Does Economic Policy Uncertainty Affect Analyst Forecast Accuracy?

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Abstract

I investigate the dynamics of analyst forecast errors relative to economic policy uncertainty (EPU) and find a significantly positive relation between EPU and analyst forecast errors. EPU's contribution to augment information asymmetry inhibits analysts' ability to forecast leading to aggravated forecast errors. A doubling of EPU increases earnings forecast errors by 4.29 percentage points, and the volatility and dispersion in forecast errors are positively related to the EPU. This effect of EPU on forecast errors persists for 13 months with a gradually declining effect that is aligned with Oi–Hartman–Abel effect, a channel through which uncertainty can affect firms' financial activities, performance, and growth. Forecast errors are higher for firms with higher sensitivity to the EPU, and the uncertainty factor retains its significance when compared to the other risk factors. Additionally, firms with higher idiosyncratic risks show a higher sensitivity to the EPU.

Keywords: EPU, economic policy uncertainty, economic uncertainty, earnings forecasts, EPS forecasts, analyst forecast errors, analyst forecast accuracy, Oi-Hartman-Abel effect

JEL Classification Codes: D80, E22, E32, E66, G10, G14, G17, G18, G30, G38

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1 Introduction

Stock analysts play a crucial role in the capital markets as they convey important information to the investors. As noted by Schipper (1991), earnings forecasts are "not a final product but rather an input into generating a final product". To elaborate this point, Bradshaw (2004) and Loh & Mian (2006) show that the analyst recommendations are dependent, at least partially, on the analyst forecasts. Analyst forecasts have a broad influence on the stock investments because both small and large investors trade based on earnings forecasts as well as analyst recommendations (Mikhail, Walther, & Willis, 2007). A natural consequence of an increase in average forecast error is a large number (and amount) of suboptimal investments resulting in a significant amount of monetary losses by many investors. As a result, a large body of academic research seeks to answer the question of what affects the analyst forecasts and recommendations. Prior studies show that several firm-specific factors, analyst characteristics, information asymmetry between firms and investors, and investor sentiment affect analyst forecast accuracy.[1] While literature shows that various microeconomic factors affect the analyst forecast errors, little attention is given on how the macroeconomic conditions affect the analyst forecast errors and when the forecast errors are likely to increase. A significant effect of macroeconomic conditions is seen in the period around 2007-2008 when many individuals and firms made incorrect decisions on their investments, incurred huge losses, and the whole economy suffered in turn. This brings up the importance of being aware of the situations or macroeconomic conditions when the analysts' earnings forecasts are likely to be less accurate.

In this study, I shed light on the effect of economic policy uncertainty (EPU) on earnings forecast accuracy. Since the recent recession, the economic uncertainty has attracted higher attention (Stock & Watson, 2012). Similarly, a growing alertness on the EPU (uncertainty

[1] See, for example, Lang and Lundholm (1996), Clement (1999), Duru and Reeb (2002), Bhattacharya, Daouk and Welker (2003), Hope (2003), Plumlee (2003), Herrmann and Thomas (2005), Chen, Ding and Kim (2010), Dhaliwal, et al. (2012), Hilary and Hsu (2013), So (2013), Walther and Willis (2013), Liang and Riedl (2014), and Keskek, et al. (2017). Section 2 contains a brief discussion on these studies.

related to economic policies including fiscal and monetary policies) is seen in many news articles, statements by the policymakers, and academic researches.[2] As mentioned by the Federal Reserve Vice Chairman Stanley Fischer:

"Uncertainty about the outlook for government policy in health care, regulation, taxes, and trade can cause firms to delay projects until the policy environment clarifies."[3]

This research is based on three sets of prior studies. The first set includes the studies on analyst forecast accuracy. Studies show that greater information uncertainty (Zhang, 2006) and an increase in return volatility (Dzielinski, 2012) produce higher forecast error. Hutton, Lee and Shu (2012) show that the analyst's earnings forecast accuracy becomes lower when management's actions and firm performance are difficult to anticipate by outsiders. For example, a firm would experience losses when it has excess capacity or increased inventory, and outsiders would know about the change in that firm's earnings after the firm's earnings report is published. Thus, it would be difficult for outsiders to anticipate the change in earnings in between two quarterly earnings reports.

The second set of studies shows that EPU affects the management's actions and firm's performance through different channels. When the economic policy uncertainty rises, consumers choose to spend less, financing opportunity for many firms reduces, overall investment opportunity decreases, and fluctuations in investment level increases (e.g., Bond and Cummins (2004), Baker, Bloom and Davis (2016), Gulen and Ion (2016), and Nguyen and Phan (2017)). Several other studies show an overall negative effect of economic policy uncertainty on the financial markets. Bloom (2009), Pástor and Veronesi (2012), Bloom (2014), and Brogaard and Detzel (2015), among others, show that the asset price reduces, stock return dampens, return volatility increases, unemployment rate rises, and the information on the firms and financial markets generate (and flow) at a reduced rate during the periods of high policy uncertainty.

[2] See, for example, *Economic uncertainty levels have hit an all-time high* (PWC Press Room, Jun 13, 2017) or *US STOCKS-Wall St slips on tax plan uncertainty, GE losses* (Reuters, Nov 13, 2017).
[3] Source: "Fed's Fischer Warns Political Uncertainty Hurts Economic Growth" (Bloomberg Politics, Jul 31, 2017).

The third set studies the Oi–Hartman–Abel effect. This effect, described by Oi (1961), Hartman (1972), and Abel (1983) and well known in the uncertainty literature, is one channel through which uncertainty can affect the investment, performance, and growth. Empirical studies in the literature have shown that the effect of uncertainty is positive in the medium and long run as firms can adjust its production over time. However, in the short run, the adverse effect of uncertainty ("inverse Oi–Hartman–Abel effect") prevails when the firms cannot fully adjust its production easily (e.g., Bloom (2014), Born & Pfeifer (2014), Senga (2015)).

By linking these three sets of studies, I conjecture a positive effect of EPU on analyst forecast errors. When a high level of EPU affects a firm's performance and earnings adversely, analysts (as outsiders) find difficulty in anticipating the firm's earnings before the firm releases its earnings reports. Additionally, during the periods of high uncertainty, fluctuations in overall investment levels and stock markets' performances create another level of difficulty for the analysts. When analysts do not get enough or reliable information that are required to predict firms' performances, prospect for making less accurate earnings forecasts increases. Thus, average forecast error becomes higher during periods of high uncertainty.

To test the effect of EPU on the earnings forecast accuracy, I use the EPU index, developed by Baker, Bloom and Davis (2016), as a proxy for policy related economic uncertainty. The EPU index is built to capture the aggregate policy uncertainty and is constructed based on the uncertainty of policy decisions found in news articles and forecasts by the economists. First, I test the impact of EPU on the average forecast errors and find that EPU has a significant effect on the earnings forecast errors. A doubling of EPU increases the average analyst forecast error by 4.29 percentage points. Second, I test the effect of firm-level EPU-sensitivity on the forecast errors and find that analyst forecast errors increase with firm-level EPU-sensitivity, and EPU-sensitivity remains significant when compared to sensitivities to other risk factors. This result suggests that earnings of firms with higher EPU-sensitivity fluctuate more during the periods of high EPU, and thus, analyst forecast errors become higher for those firms. Third, I find that the volatility of forecast errors (standard deviation of forecast errors) and dispersion in forecast errors (difference between 75th and 25th percentile of forecast errors) are directly related to the EPU. This result is aligned with the higher fluctuations in investments following high EPU (Gulen & Ion, 2016) that is suggestive of fluctuations in other financial activities as well.

To rule out concerns about unobserved effects, omitted variables, seasonality, and endogeneity, I use fixed effects in the main tests and run a series of robustness tests. First, I use fixed effects in all the regressions to control for unobserved effects of firm and time. To check on whether other macroeconomic variables are driving the result, I add several other macroeconomic controls in the model to find if EPU is capturing other macroeconomic conditions. Following Gulen and Ion (2016), and Nguyen and Phan (2017), I use several proxies of macroeconomic condition and macroeconomic uncertainty separately as well as together in my base model. To ensure that one of the three quarter-months is not driving the results, I run separate regressions for the three quarter-months. Finally, following Gulen and Ion (2016), and Nguyen and Phan (2017), I check for endogeneity issue by using the residual of regression of USA EPU on the Canada EPU as an instrumental variable in the regression of analyst forecast errors.[4] All these tests show a positive and significant effect of EPU on the earnings forecast error. Thus, results of these tests endorse the main results of the study.

I extend the empirical analysis in four more directions. First, I check whether the effect of EPU on forecast error is specific to some industries. The effect of EPU on analyst forecast errors is positive and significant for manufacturing, energy, chemicals, business equipment, and shops industries. This result suggests that EPU affects earnings of firms in these industries more compared to earnings of firms in other industries.

Second, I examine whether the effect of EPU on the analyst forecast errors is related to certain firm characteristics. Results show that smaller firms are more sensitive to economic

[4] Based on the idea that the USA and Canada economies are strongly linked, the residual (from regression of USA EPU on the Canada EPU) would be devoid of the macroeconomic shocks common to these two economies, and hence, it can serve as an appropriate instrumental variable.

policy uncertainty, and they are subject to higher analyst forecast errors compared to larger firms. This result is intuitive as the smaller firms find problem in financing in general (Lemmon & Zender, 2010), and those firms find more problem in financing during the periods of high uncertainty as investors are less likely to invest in risky firms at that time (Brogaard & Detzel, 2015; Tran & Phan, 2017).

Third, I investigate the progressive effect of EPU on forecast errors over time. Results show that the positive and significant effect of EPU on future analyst forecasts persists for 13 months. This effect of EPU decreases gradually over time and becomes insignificant after 13 months. The effect of EPU persists for a few months because the activities in the financial markets do not stabilize instantaneously after the high EPU resolves. Rather, once the high uncertainty is dissolved, the financial markets' activities become normal over time, and analysts start to receive gradually increased information in the process. As the analysts receive more and more information, accuracy of their earnings forecasts increases over time. This finding is consistent with the study by Gulen and Ion (2016) that shows that, the effect of EPU on both the level of investments and fluctuations in investment level persists for many months after the high EPU resolves.

Finally, I study the interaction effect of various financial and macroeconomic business cycles to check the effect of EPU during different phases of business cycles. Test results indicate that the default spread, TERM spread, dividend yield, and industrial production growth have significant interaction effects on the forecast errors. I check the effect of EPU during recession and non-recession time using NBER recession indicators (recession indicator is zero during peak and recession indicator is one during trough). The effect of EPU is significant during both peak and trough periods, and economic significance is highest during the trough. This implies that the effect of EPU on analyst forecast accuracy is the highest when a period of high policy uncertainty coincides with a recession period.

This study emphasizes that EPU has a potentially significant implication on the stock market investments. During the periods of high EPU, higher errors in earnings forecasts increase the potential for inaccurate stock recommendations because analyst recommendations are at least partially dependent on the analyst forecasts (Bradshaw, 2004; Loh & Mian, 2006). Therefore, whenever an investor makes investment decision based on earnings forecast or analyst recommendation, the prospect for suboptimal investment and subsequent monetary loss increases during high EPU periods. Both the small and the large traders may make suboptimal investments during the periods of high EPU because both the types of investors invest based on earnings forecasts and analyst recommendations (though in varying degrees). However, the possibility of making suboptimal investments is higher for the small or unsophisticated investors because they act upon any published recommendation (Mikhail, Walther, & Willis, 2007). The economic implication of this study lies with the fact that significant monetary loss of many investors in the same period is likely to lead to a recession. Additionally, this study indicates that the firms are not equally sensitive to the economic policy uncertainty, and the forecast errors depend on the firm-level EPU-sensitivity. While the study shows the effect of EPU on the forecast errors, as mentioned by Bloom (2014) and Baker, Bloom and Davis (2016), causality of EPU is not clear yet.

This study is related to four streams of studies. The first stream includes the studies on the analyst forecast accuracy that show how various factors affect the analyst forecast accuracy. The second stream documents the impact of uncertainty on different aspects of financial markets. The third stream specifically investigates the effects of economic policy uncertainty. The fourth stream studies the channels (including Oi-Hartman-Abel effect) through which uncertainty affects the financial activities. This study contributes to all these four streams of studies by showing the effect of economic policy uncertainty on the analysts' earnings forecast accuracy and by providing further support to "inverse Oi-Hartman-Abel" effect in the short run.

The remaining parts of the paper are organized as follows. Section 2 comprises of literature review that narrates the motivation behind the study and leads to hypotheses development. Section 3 describes the sample construction and empirical methods. Section 4 demonstrates the empirical analyses and Section 5 concludes.

2 Literature Review and Hypotheses Development

The analyst forecast literature documents various micro level factors that influence the analyst forecast accuracy. Studies show that analyst forecast error is positively related to firm size, book-to-market value of equity, debt-to-equity ratio, momentum, change in earnings, earnings volatility, earnings skewness, and international diversification, and negatively related to return standard deviation (Duru & Reeb, 2002; So, 2013; Liang & Riedl, 2014). Mansi, Maxwell, and Miller (2011) document that the impact of the analysts is the largest in magnitude when uncertainty about firm value is the highest. Other studies manifest that firm complexity, financial opaqueness, disclosure practices of firms, and firms' political connection and corruption affect the analyst forecast accuracy (Lang & Lundholm, 1996; Bhattacharya, Daouk, & Welker, 2003; Hope, 2003; Chen, Ding, & Kim, 2010; Dhaliwal, Radhakrishnan, Tsang, & Yang, 2012).

Analyst forecast error is impacted by analyst characteristics as well. Clement (1999), Herrmann and Thomas (2005), and Dhaliwal et al. (2012), among others, show that analysts' experience, analysts' employer size, numbers of firms and industries followed by the analysts, analyst's experience with a firm, forecast frequency, and forecast horizon affect the forecast accuracy. Hilary and Hsu (2013) document that the consistency in an analyst's forecast has the ability to affect prices. Keskek et al. (2017) suggest that an analyst's ability to generate private information affects the forecast accuracy.

Some other studies on the analyst forecast show that the forecast accuracy is impacted by information complexity (Plumlee, 2003), information asymmetry between firms and investors (Chen, Ding, & Kim, 2010), and investor sentiment (Walther & Willis, 2013). Hutton, Lee and Shu (2012) that show that the analyst's earnings forecast accuracy becomes lower when management's actions and firm performance are difficult to anticipate by outsiders. Using the dispersion in analyst forecasts as a proxy for information uncertainty, Zhang (2006) shows that greater information uncertainty produces higher forecast error. Though the analyst forecast literature contains many studies on the effect of microeconomic variables on analyst forecast accuracy, little attention is given upon when, how, and to what extent macroeconomic conditions affect analyst forecast errors. This gap in the analyst forecast literature sets out a broad channel of investigation to probe the effect of macroeconomic conditions on the analyst forecast errors. I choose to investigate on the effect of EPU on analyst forecast accuracy for two reasons. First, I attempt to bridge the gap in analyst forecast literature at least partially. Second, growing attention on economic policy uncertainty in the last decade makes it important to investigate the effect of EPU on the analyst forecast errors.

During periods of uncertainty, economic agents become apprehensive about the future outcomes of investments because financial factors (required to evaluate the investments) become unpredictable. In which direction will the interest rate, tax rate, and inflation rate change and what will be the magnitude of the changes? If a firm builds a new plant and demand of its products decreases afterwards, the firm will have to bear a loss. If an individual takes a mortgage to buy a house and the house price drops (along with the reduced demand of houses in the market) after buying it, the individual will incur a considerable loss. As investments are irreversible at least partly (Bernanke, 1983; Demers, 1991; Rodrik, 1991), and investors have the option of choosing their investment timing, they tend to delay their investments, particularly the long-term and risky ones, when they face uncertainty about the outcomes (Dixit & Pindyck, 1994).

Uncertainty raises divergence of opinion. Though the opinions and findings on the effect of uncertainty are not univocal, the overall effect of uncertainty on the financial markets is negative. Miller (1977) proposes the possibility of lower expected returns for risky securities when the divergence of opinion is high due to uncertainty. Jiang, Lee, and Zhang (2005) show that the firms with higher information uncertainty are subject to lower expected returns. Other studies show that, uncertainty induces a lower consumer spending and consumption (Bansal & Yaron, Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles, 2004), reduced asset value and stock returns (Diether, Malloy, & Scherbina, 2002; Bansal, Khatchatrian, &

Yaron, 2005; Ozoguz, 2009), an increase in return volatility (Dzielinski, 2012), and a decrease in asset liquidity (Minton & Schrand, 1999).

EPU literature as well documents adverse effects of EPU on the financial markets. Studies show that, when the aggregate level of policy uncertainty becomes high, consumers as well as businesses tend to delay their spending and investment, overall investment level lowers, and fluctuations in investments increase (Bond & Cummins, 2004; Bloom, 2014; Baker, Bloom, & Davis, 2016; Gulen & Ion, 2016; Nguyen & Phan, 2017). The decreased market demand, a resultant effect of the reduced consumer spending, has an additional negative impact on the firms. Firms, particularly the risky ones, tend to issue short-term debt instead of long-term debt, and they face fewer sources of funding as investors become reluctant in putting their money into risky firms (Tran & Phan, 2017). Unemployment rate and volatility in unemployment rate increase during higher uncertainty (Caggiano, Castelnuovo, & Figueres, 2017) as firms lay off employees and delay hiring new employees. Other studies show that asset price reduces, stock return dampens, return volatility increases, unemployment rate rises, and the information on the firms and financial markets generate (and flow) at a reduced rate during the periods of high policy uncertainty (Bloom, 2009; Pástor & Veronesi, 2012; Antonakakis, Chatziantoniou, & Filis, 2013; Bloom, 2014; Brogaard & Detzel, 2015; Liu & Zhang, 2015). Thus, EPU affects the financial markets in various ways.

Uncertainty is seen to appear and increase after major economic and political shocks, and uncertainty shocks normally generate short sharp recessions (Bloom, 2009). However, uncertainty is not always associated with recessions. The fiscal cliff (debt ceiling standoff) in 2011 generated the highest uncertainty in the history resulting in poor performances in the financial market. However, the uncertainty was not accompanied or followed by a recession at that time.

A part of uncertainty literature includes the studies on Oi–Hartman–Abel effect (Oi, 1961; Hartman, 1972; Abel, 1983). This effect is one channel through which uncertainty can affect the investment, performance, and growth. Empirical studies in the literature have shown that the effect of uncertainty is positive in the medium and long run as firms can adjust its production over time. However, in the short run, the adverse effect of uncertainty ("inverse Oi–Hartman–Abel effect") prevails when a firm cannot fully adjust its production easily (e.g., Bloom (2014), Born & Pfeifer (2014), Senga (2015)). Bloom (2014) argues that firms cannot adjust their production in the short run because of adjustment costs. To satisfy the market demand, firms become stuck to sell their products either lesser in quantity at their preset prices or more in quantity at lower prices (Born & Pfeifer, 2014). Unable to adjust production in a short period of time, firms face lower earnings in the short run.

When a high level of EPU affects a firm's performance and earnings adversely, analysts (as outsiders) find difficulty in anticipating the firm's earnings before the firm releases its earnings reports. Additionally, during the periods of high uncertainty, fluctuations in overall investment levels and stock markets' performances create another level of difficulty for the analysts. When analysts do not get enough or reliable information that are required to predict firms' performances, the potential for making less accurate earnings forecasts increases. Therefore, I expect that average errors in earnings forecast will become higher during the periods of higher uncertainties and develop the first hypothesis as follows.

Hypothesis 1: *Analyst forecast error increases in economic policy uncertainty.*

While I expect that EPU affects firms' earnings and performances, I do not expect all firms to have similar sensitivity to economic policy uncertainty. Firms with higher sensitivity to economic policy uncertainty will exhibit higher uncertainty in their performance and earnings compared to the firms with lower sensitivity to economic policy uncertainty. This will result in higher analyst forecast errors for firms that are more sensitive to the economic policy uncertainty. This implies the following.

Hypothesis 2: *Analyst forecast error increases in firm-level sensitivity to economic policy uncertainty.*

As economic policy uncertainty is associated with a divergence of opinions, I expect to see higher variability in analyst forecast errors during periods of high uncertainty. Additionally, I expect firms with high idiosyncratic risks have higher sensitivity to economic policy uncertainty and they are subject to a higher analyst forecast compared with firms with low idiosyncratic risks. So, I develop two secondary hypotheses as follow.

Hypothesis 3: *Volatility and dispersion in analyst forecast error increase in economic policy uncertainty.*

Hypothesis 4: *Firms with high idiosyncratic risk have high sensitivity to economic policy uncertainty and are subject to higher forecast error.*

3 Data and Methodology

3.1 Sample

To match the data availability and to avoid error-prone data, the sample period for the study is chosen to be from 1994 to 2015. The analyst forecasts were recorded in the Institutional Brokers' Estimate System (I/B/E/S) in batch until the beginning of 1990's and hence there might be some errors in analyst forecast dates in the period before 1994 (Clement & Tse, 2003; Hilary & Hsu, 2013). I end the sample in 2015 because annual reports in Compustat annual database are available until 2015 at the time of this study.

As a proxy for policy related economic uncertainty, I use the monthly "baseline overall economic policy uncertainty index" that is developed by Baker, Bloom, and Davis (2016) and available at the economic policy uncertainty website. Figure 1 shows the graphical presentation of the economic policy uncertainty (EPU) index along with recession indicators. The EPU index is a proxy for uncertainty related to future economic policies (including fiscal and monetary policies), and it is designed to capture uncertainty about who will make economic policy decisions, what economic policy actions will be undertaken and when, and the economic effects of policy actions. The EPU index is constructed as a weighted average of four components: the new component, the tax component, consumer price index (CPI) component, and the government expenditure component. Appendix A contains more details on the EPU Index.

From the Center for Research in Security Prices (CRSP), I obtain the monthly return (*RET*) data between 1989 and 2016 for all the CRSP firms that trade on the NYSE, AMEX, or NASDAQ exchanges. To run 60-month rolling window regressions on stock returns from 1994, I need data starting from 5 years before the sample start date, so I collect data from the CRSP database from 1989 onwards. As analyst forecasts are relevant for the public firms, I consider firm age as its age since IPO, and use start date of price data (*ST_DATE*) for the sample firms from the CRSP database to calculate the firm age. I also obtain the price and number of shares outstanding from the CRSP database to calculate the market value of equity.

This study is centered on the analyst forecasts for earnings per share (EPS). I collect the one quarter ahead ($FPI = 6$) analyst forecasts for the earnings per share (*VALUE*) and the actual values of the earnings per share (*ACTUAL*) from the I/B/E/S Detailed History database on earnings per share for US firms. To find the forecast horizon, I obtain the forecast announcement dates (*ANNDATS*) and the actual announcement dates (*ANNDATS_ACT*) from the same Detailed History database. US listed firms report their earnings during the earnings season, i.e., within two weeks of end of quarter. Consistent with prior studies (Herrmann & Thomas, 2005; Keskek, Myers, Omer, & Shelley, 2017), I consider the forecasts that have forecast horizons between 10 and 100 calendar days before the actual earnings announcement dates to include the forecasts made within 1 to 90 days before the quarter-ends and to avoid the influence of the stale forecasts on the results. As economic policy uncertainty is expected to affect each earnings forecast and small investors act upon a recommendation (and forecast) whenever is it published, the sample includes all the valid earnings forecasts that are made within the sample period.

I obtain data from the Compustat annual fundamental database to construct the firm-level control variables; details on those are described in section 3.2. I extract firm fundamental data beginning from 1989, i.e., five years before the sample starts, to obtain five-year rolling-window earnings standard deviations from the beginning of the study sample period.[5]

The data library of Kenneth R. French is the source of the monthly data on the Fama-French three-factors (Fama & French, Common risk factors in the returns on stocks and bonds, 1993) and the Fama-French five-factors (Fama & French, 2015) that I use in the second part of the main empirical analysis.

At the intersection of the CRSP, Compustat, and IBES, the sample consists of 8,853 firms, 415,900 firm-month observations, and 1,490,961 analyst forecasts over the sample period of 264 months.[6] The sample used in the study has only those observations that have non-missing forecast error data at time t and non-missing independent variables data at time $t-1$. To remain in the sample, I require the firms to have an age of at least one year because an analyst's forecast for a firm without sufficient public history is likely to be noisy. To avoid the influence of the extreme outliers, I Winsorize all the ratio variables with absolute values (with one tail) at the 98th percentile and other ratio variables (with two tails) at the 1st and 99th percentiles. Panel A of Table 1 shows the descriptive statistics of the main variables. The table includes the main variables analyst forecast errors and EPU index along with firm-level control variables stock returns, book-to-market value of equity, leverage (ratio of debt to debt + equity), annual change in earnings, and earnings standard deviations.

[5] I use a five-year rolling-window to construct earnings standard deviation to avoid survivorship bias, i.e., many firms do not survive beyond the Compustat-firms' average age of 7 years, and those firms get deleted from the sample if a longer window is used to calculate values in a rolling-window. However, use of a 10-year rolling-window does not change the results qualitatively.

[6] Disclaimer: Data extracted, and all the tests are done before my licenses for CRSP, Compustat, and IBES databases expired in September 2018.

Panel B of Table 1 reports the correlation between EPU index and some alternate measures on general economic condition and economic uncertainty. Alternate measures on the general economic condition are the real Gross Domestic Product, forecasts for GDP growth rate, the Leading Index for the United States, the Composite Leading Indicators, and the Financial Stress Index. Alternate measures on the economic uncertainty are the dispersion in forecasts for GDP growth rate, the Volatility Index VXO, monthly cross-sectional standard deviation of stock returns, and JLN uncertainty measure (Jurado, Ludvigson, & Ng, 2015). Appendix B contains details on these variables. Purpose of this table is to see whether any of these alternate macroeconomic measures may have some explanatory power on EPU index. Here, it can be observed that the correlation between the EPU index and most of the other economic measures is moderate to high. This raises the concern on whether earnings forecast error is affected by some economic factor(s) other than EPU. I address this concern in my empirical study as described in section 4.7.

The study includes three types of business cycles: financial business cycles, macroeconomic business cycles, and economic condition. Following Petkova and Zhang (2005) and Belo, Gala and Li (2013), I use the financial business cycles default spread (DEF), term spread (TERM), risk-free interest rate (TB), and dividend yield (DIV. Following Belo, Gala and Li (2013), I use the macroeconomic business cycles that are not based on financial price data or other data at the micro level. Macroeconomic business cycles used in the study are the inflation rate, unemployment rate, and industrial production growth rate. The last business cycle is the NBER recession indicator data. Details on all these business cycles are available in Appendix C.

3.2 Variables

The main variables of my interest are the analyst forecast error and the economic policy uncertainty index. I calculate the analyst forecast error as the absolute value of difference between actual and forecast EPS divided by the actual EPS as shown below.[7] To avoid influence of extreme outliers on the results, I trim the top two percentiles of the analyst forecast errors.

$$FCE = abs\left(\frac{Actual - Forecast}{Actual}\right)$$

Control variables used in the study are as follows: past returns, book-to-market value of equity (BE/ME), leverage, change in earnings (ΔEarnings), and earnings standard deviation. I use change in earnings and earnings standard deviation to capture the short-term variations in earnings and long-term variations in earnings, respectively. Appendix A contains details on how all these variables are constructed.

For easier comparison and interpretation of the economic magnitudes across variables in the regressions, I standardize all variables using their sample means and standard deviations. The results can be interpreted as one standard deviation change in an independent variable is associated with a change in the dependent variable by the independent variable's coefficient times the dependent variable's standard deviation (with all else equal).

3.3 Research Design

The main empirical analysis of the study consists of tests on the two primary hypotheses. To test the first hypothesis, I focus on the effect of economic policy uncertainty on the average analyst forecast error. The panel regression model used for the test, as shown in equation 1, is consistent with the analyst forecast literature.

$$FCE_{i,t} = \alpha_1 + \alpha_2 \times EPU_{t-1} + \alpha_3 \times MnDm + \alpha_n \times CV_{n,i,t-1} + FE + \varepsilon_{i,t} \qquad (1)$$

Here, firms are denoted by i and calendar months are denoted by t. In the regression, all independent variables have lag of one month from the dependent variable analyst forecast error

[7] I find unchanged statistical significance and increase economic significance when I use the alternate measure of forecast error as the absolute value of difference between actual and forecast EPS divided by the price.

($FCE_{i,t}$). I measure the dependent variable $FCE_{i,t}$ as the average of all analyst forecast errors for a firm (i) in a month (t). $EPU_{i,t-1}$ is the natural logarithm of the economic policy uncertainty index in the month *t–1*. The notation $CV_{n,i,t-1}$ is the set of firm-specific control variables where *n* indicates different control variables used in the regressions. Following the analyst forecast literature, I use the commonly used firm-specific control variables: average return over the last 12 months, book-to-market value of equity, leverage, change in annual earnings over the year, and standard deviation of earnings over last 5 years. To reduce the chance that the relationship between analyst forecast error and economic policy uncertainty is driven by an (or some) unobserved effect(s), I use several sets of fixed effects (denoted by *FE*) to test the model (Petersen, 2009). Analyst forecast literature shows that the analyst forecast accuracy is influenced by various firm-specific characteristics (e.g., firm complexity, international diversification, etc.) as well as various analyst-specific characteristics (e.g., experience, number of firms following, etc.) which are not included in the regression model specifically but handled with the use of fixed effects. The fixed effects used in the empirical tests include the firm fixed effects (to include omitted firm-specific control variables) and industry-year fixed effects (to consider the industry specific shocks in a given year).[8] I do not include analyst fixed effects here as I use forecast errors averaged at the firm-month level. I do not consider time fixed effects here as the EPU measure is the same for all the firms in a given month, and thus, inclusion of time fixed effects would automatically absorb the explanatory power of economic policy uncertainty. To consider the time effects, however, I use the month dummies (*MnDm*) in the regressions. There is a possibility that the test results are driven by some other macroeconomic variables; to alleviate this concern, I add several measures on general economic condition and economic uncertainty to the baseline model (equation 1) and check for the explanatory power of economic policy uncertainty. Details on these tests along with analysis of the results are discussed in section 4.6.

[8] For all the test results reported here, four-digit SIC code is used as industry classification. In unreported results, I have used Fama-French 12- and 48-industry group industry classifications in the tests and found no qualitative changes in the test results.

To verify the second hypothesis, I test the effect of heterogeneity in firm-specific EPU-sensitivity on analyst forecast accuracy. First, I derive the firm-specific EPU-sensitivity by regressing excess return of the firm on the magnitude of monthly changes in EPU (denoted by ΔEPU_t) on 60-month rolling windows.[9] To reduce the chance of results arising from one particular model, I construct the model in two different ways. In one model, I add the three factors of Fama and French (1993) and in the other model, I add the five factors of Fama and French (2015) as shown in equations 2a and 2b, respectively. In the equations below, $R_{i,t}$ is the stock return of firm *i* at month *t* and $R_{f,t}$ is the risk-free rate of return at month *t*. Market factor (MKT_t) is the difference between the return on the value-weighted market portfolio and the risk-free rate of return at month *t*. The factor SMB_t is the difference between the return on a diversified portfolio of small stocks and the return on a diversified portfolio of big stocks. The factor HML_t is the difference between the returns on diversified portfolios of high book-to-market and low book-to-market stocks. The factor RMW_t is the difference between the returns on diversified portfolios of stocks with robust and weak profitability. The factor CMA_t is the difference between the returns on diversified portfolios of low investment stocks (conservative) and high investment stocks (aggressive). I obtain the firm-specific EPU-sensitivity measure as the coefficient of ΔEPU_t (i.e., $\beta_{E,i,t}$) for each firm-month separately from the models specified in 2a and 2b.

$$R_{i,t} - R_{f,t} = \beta_1 + \beta_{E,i,t} \times \Delta EPU_t + \beta_{M,i,t} \times MKT_t + \beta_{S,i,t} \times SMB_t + \beta_{H,i,t} \times HML_t + e_t \tag{2a}$$

$$R_{i,t} - R_{f,t} = \beta_1 + \beta_{E,i,t} \times \Delta EPU_t + \beta_{M,i,t} \times MKT_t + \beta_{S,i,t} \times SMB_t + \beta_{H,i,t} \times HML_t + \beta_{R,i,t} \times RMW_t + \beta_{C,i,t} \times CMA_t + e_t \tag{2b}$$

[9] I have also used 12-month and 24-month rolling window regressions to check the results in different ways and found that the significance of the results persists.

Next, I test the effect of firm-specific EPU-sensitivity ($\beta_{E,i,t}$) on analyst forecast error by replacing EPU_{t-1} by $\beta_{E,i,t-1}$ in equation 1. The model used at this step is as shown in equation 3 below. In this test also, I use the same set of control variables and all the fixed effects mentioned earlier for equation 1. As I obtain different EPU-sensitivity measures for the firms in any given month, here I use year fixed effect instead of month dummy. I also use the analyst fixed effect here as individual forecast errors are included in the regression.

$$FCE_{i,t} = \gamma_1 + \gamma_2 \times \beta_{E,i,t-1} + \gamma_n \times CV_{n,i,t-1} + FE + \varepsilon_{i,t} \quad (3)$$

To test the third hypothesis, I calculate standard deviation of the analyst forecast errors in each month as a measure of volatility of the analyst forecast errors. Dispersion in analyst forecast errors is measured as the difference between the 75th and 25th percentiles of analyst forecast errors. Next, I divide the EPU into quintiles, and get the univariate statistics of analyst forecast errors in each EPU quintile.

I test the fourth hypothesis by considering risk characteristics of individual firms. Here, I measure idiosyncratic risk as the standard deviation of the regression residuals obtained from the market model.[10] To reduce the impact of small sample on the statistical power of the results, I require a minimum of 15 daily return data and non-zero trading volume in a month. To obtain the standard deviation at monthly level, I multiply the standard deviation of daily residuals by the square root of the number of observations in that month. I obtain the sensitivity to EPU from model 2a. First, I check whether the sensitivity to EPU is higher for the firms with high idiosyncratic risk. Next, I check whether analyst forecast error increases with the increase in idiosyncratic risk. To test these two cases, I create idiosyncratic risk quintile and obtain the univariate statistics of sensitivity to EPU and analyst forecast error in each risk quintile.

[10] Results do not change qualitatively when residuals from 3-factor model or 5-factor model are used.

To address the concerns on omitted macroeconomic variables, I augment the baseline model by adding various macroeconomic variables as shown below. The term MV_{t-1} denotes the macroeconomic variables that I use in the tests.

$$FCE_{i,t} = \alpha_1 + \alpha_2 \times EPU_{t-1} + \alpha_3 \times MnDm + \alpha_n \times CV_{n,i,t-1} + \alpha_m \times MV_{t-1} + FE + \varepsilon_{i,t} \quad (4)$$

To obtain unbiased estimates, I cluster the standard errors in multiple dimensions (Petersen, 2009; Cameron, Gelbach, & Miller, 2011) and report the cluster-robust standard errors. In the test results shown here, I cluster the standard errors by firm and year. In unreported results, I verify the results by standard error clustering on other variables as well.

4 Empirical Analysis

4.1 Effect of Economic Policy Uncertainty on Analyst Forecast Errors

I start the empirical tests by regressing analyst forecast error at firm-month level on the economic policy uncertainty index using the multivariate model shown in equation 1. While there is no mechanical relation between the economic policy uncertainty and the analyst forecast errors, question may arise on whether the analyst forecast error influences the economic policy uncertainty though there is no evident reason to believe so. To reduce the reverse causality concern, I lag the EPU measure (and its components, wherever those are used) by one month in the tests throughout.

Panel A of Table 2 shows the regressions on EPU level, changes in EPU (measured as $EPU_{t-1} - EPU_{t-2}$), and natural logarithm of EPU. Results show that the expected signs of the coefficients match the observed signs of the coefficients. Supportive to my hypothesis 1, all of the EPU level, changes in EPU, and log of EPU have a positive effect on the magnitude of analyst forecast error. The effects of EPU level, changes in EPU, and log of EPU on the analyst forecast errors are significant at the 5% level, 10% level, and 1% level, respectively. One standard deviation change in EPU level, changes in EPU, and log of EPU are associated with analyst forecast error changes by 0.0311, 0.0128, and 0.0328 standard deviations, respectively. This can be interpreted as 1-unit change in EPU level is associated with 0.0407-unit change in analyst forecast error, and a doubling of EPU level changes the analyst forecast errors by 4.29 percent points.[11] This is economically significant considering the changes in the EPU during the economic downturns are quite high in general.

Panel B of Table 2 shows the separate regressions on the four components of EPU after their logarithmic transformations. Results show that all of the EPU components have positive effect on the analyst forecast errors. The news component is significant at the 5% level, the government expenditure component is not significant, and the inflation and tax components are significant at the 1% level. One standard deviation change in news component, government expenditure component, inflation component, and tax component are associated with analyst forecast error changes by 0.0204, 0.0222, 0.0326, and 0.0431 standard deviations, respectively. This means that 1% change in the news, government expenditure, inflation, and tax components are associated with the analyst forecast error changes by 0.0267, 0.0290, 0.0427, and 0.0564 percent points, respectively. This table shows that the analyst forecast errors are impacted more by the policy uncertainties related to inflation and tax compared with other policy related uncertainties. Lower economic and statistical significances of the news component suggest that a part of the news component does not affect the analyst forecast errors. It is possible that, while the news component is capturing uncertainties on various economic policies, some of those have a little effect on the financial market activities. Insignificant government component suggests that the uncertainty about government expenditure, which includes uncertainties about expenditures at federal, state, and municipal levels, has no substantial effect on the analyst forecast errors.

[11] When I measure the forecast error as the absolute value of difference between actual and forecast EPS divided by the price, I find that a doubling of EPU level changes the analyst forecast errors by 6.67 percent points that is significant at 1%.

Overall, the results in Table 2 show that the economic policy uncertainty has significant effect on analyst forecast errors after controlling for various factors on firm, industry, and time. An increased economic policy uncertainty affects firms' earnings and performance, and it also increases uncertainty about the firm's earnings. As analysts find difficulty in anticipating a firm's earnings before the firm publishes its earnings reports, possibility for making earnings forecast errors increases. Thus, it is reasonable to state that the economic policy uncertainty has a positive and significant impact on the analyst forecast error.

4.2 Firm-level Sensitivity to Economic Policy Uncertainty

Are all firms equally sensitive to economic policy uncertainty? If not, does firm-level EPU-sensitivity affect the level of analyst forecast errors? To answer these questions, first I obtain the firm-level EPU-sensitivity in each month by regressing the firm-level excess stock return on the changes in EPU in 60-month rolling window regressions using the models shown in equations 2a and 2b. Next, I regress analyst forecast errors on the firm-level EPU-sensitivity using the model shown in equations 3. Here I use the individual analyst forecast errors so that I can control for analyst fixed effects while I check for firm-level EPU-sensitivity. Panel A and panel B of Table 3 show the results of the regressions of analyst forecast errors on sensitivity measures obtained from model 2a and 2b, respectively. Using different sets of fixed effects, I show that the effect of the firm-level EPU-sensitivity on the analyst forecast errors is consistently positive and significant at the 0.1% level. In support of hypothesis 2, the results show that the analyst forecast errors are higher for the firms that have higher sensitivity to EPU.

I augment my tests in this part by checking on whether sensitivity to other risks factors (i.e., $\beta_{M,i,t}$, $\beta_{S,i,t}$, $\beta_{H,i,t}$, $\beta_{R,i,t}$, and $\beta_{C,i,t}$ from equations 2a and 2b) have effects on analyst forecast errors. For each of the risk factors used in 3-factor and 5-factor models, I run three regressions by adding to equation (3) the sensitivity to the risk factor first, interaction between the EPU-sensitivity and other risk sensitivity next, and both the risk sensitivity and interaction term in the last regression. Panel C shows the regression results for the risk factors in 3-factor model and panel D shows the regression results for the risk factors in 5-factor model. In all these tests, significance of sensitivity to EPU prevails after controlling for sensitivity to other risk factors.

Next, I extend my analysis on firm-level EPU-sensitivity to look into which type(s) of firms are more sensitive to the economic policy uncertainty and subject to higher analyst forecast errors. Do firms in some industries exhibit high EPU-sensitivity? Is there any relation between EPU-sensitivity and certain firm characteristics? To investigate on these, first, I classify firms based on industry segment, size, and capital structure. Next, I examine whether the firm-level EPU-sensitivity and the effect of EPU on forecast errors vary across these groups. Empirical analyses on these are elaborated in the subsections 4.2.1 and 4.2.2 as follow.

4.2.1 Industry Heterogeneity

Here, I classify the industry using Fama-French 12-industry groups and use the regression model of equation 1 for each industry group separately. For brevity, I report the results only on the variables of interest from here onwards. Results in Table 4 show that the effect of EPU-sensitivity on analyst forecast error is positive and significant for manufacturing, energy, chemicals, business equipment, and shops industries. This result suggests that uncertainty in earnings for firms in these industries increases with the increase in change in EPU. However, this result does not indicate that EPU-sensitivity or forecast error would be higher for firms in these industries. In a separate unreported test, I find that the forecast error is highest for the energy industry whereas the EPU-sensitivity is the highest for the business equipment industry.

4.2.2 Firm Size and Capital Structure

I measure firm size by the total assets of the firm and capital structure as the ratio of total debt and common equity. In this part, I consider the statistics of EPU-sensitivity and analyst forecast error in the firm size and debt-to-equity ratio quintiles to find the trend of EPU-sensitivity clearly. First, I create quintiles of firm size and debt-to-equity ratio, and then I obtain the univariate statistics of EPU-sensitivity and analyst forecast error in each quintile of firm size and debt-to-equity ratio. Panels A1 and A2 of Table 5 present the EPU-sensitivity statistics and analyst forecast error statistics, respectively, in firm size quintiles. Panels B1 and B2 of Table 5 present the EPU-sensitivity statistics and analyst forecast error statistics, respectively, in debt-to-equity ratio quintiles. Dispersion is measured as the difference between the 75th and 25th percentile statistics in each quintile. In panels A1 and A2, it can be observed that all the statistics (mean, standard deviation, quartile 1 measure, median, quartile 3 measure, and dispersion in EPU-sensitivity) of EPU-sensitivity and forecast errors decrease as the firm size and debt-to-equity ratio increases. Differences between the statistics in the 5th and 1st quintiles (Hi − Lo) are negative for all the statistics, and the dispersion in each quintile is positive in both the panels A1 and A2. A similar pattern can be observed in panel B1 that reports EPU-sensitivity statistics in debt-to-equity ratio quintiles. However, panel B2 reports no clear trend of analyst forecast error statistics in debt-to-equity ratio quintiles. Most of the smaller firms are start-ups and they raise funds by issuing equity as they have less access to debt (Lemmon & Zender, 2010). Thus, it is possible to have a considerable overlap between the quintile 1 of size quintiles and quintile 1 of debt-to-equity quintile for my sample. Overall, results of Table 5 convey that the smaller firms are more sensitive to the economic policy uncertainty, and they are subject to higher analyst forecast errors compared to the large firms. Firms with lower leverage also exhibit higher sensitivity to the economic policy uncertainty. However, firms with very high as well as very low leverage are subject to higher analyst forecast errors whereas firms with medium leverage are subject to lower forecast errors. This shows an interesting relation between analyst forecast error and capital structure in connection with economic policy uncertainty.

4.3 Seasonality in Analyst Forecast Errors

In the monthly analyst forecast errors for the sample period, a clear seasonality is observed in analyst forecast errors (figure unreported). In each calendar-quarter, average analyst forecast error is the lowest in the first month and highest in the third month. The natural question arises, is the seasonality driving the result? To check on this, I regress separately for the three quarter-months using the baseline model. Table 6 presents the results of these three regressions under specifications 1 to 3 for calendar-quarter-months 1 to 3, respectively. It can be observed that the influence of EPU on analyst forecast error is positive and significant in each of the three quarter-months. When compared with the results in Table 2, it can be found that the magnitudes and t-statistics of the EPU coefficients in Table 6 are qualitatively similar to those obtained in Table 2. A doubling of EPU changes the analyst forecast errors by 4.42, 4.28, and 4.03 percentage points in calendar-quarter-months 1 to 3, respectively. Thus, it can be stated that seasonality in the analyst forecast errors is not driving the results.

4.4 Volatility and Dispersion in Analyst Forecast Errors

Table 7 shows the univariate statistics of analyst forecast errors in the EPU quintiles. Ancillary to hypothesis 1, the average forecast error increases monotonically from the first quintile to fifth quintile, and the difference between the fifth and first quintile forecast errors is positive and statistically significant at the 0.1% level. Supportive to the hypothesis 3, results show that the standard deviation of the analyst forecast errors increases from first quintile to fifth quintile. Dispersion, the difference between the 75^{th} and 25^{th} percentile statistics within each quintile, also increases consistently from first quintile to fifth quintile. Thus, corroborative to the hypothesis 3, the univariate statistics in Table 7 verify that both the volatility and dispersion in analyst forecast errors increase as economic policy uncertainty increases. The possible reason behind this result is the fluctuations in many financial activities that create greater divergence in analysts' opinions and generate a higher variability in forecast errors during the periods of high uncertainty.

4.5 Firms with High Risk

To verify the fourth hypothesis, I create idiosyncratic risk quintiles first. Next, I obtain the univariate statistics of sensitivity to EPU and analyst forecast error in each risk quintile. Panels A and B of Table 8 present the univariate statistics of sensitivity to EPU and analyst forecast error, respectively, in idiosyncratic risk quintiles. Results show that both the EPU-sensitivity and analyst forecast errors increase uniformly from the first quintile to fifth quintile. Also, it can be observed that, the standard deviation and dispersion (difference between the 75th and 25th percentile statistics within each quintile) in both the EPU-sensitivity and analyst forecast errors increase from first quintile to fifth quintile. Thus, we can see that, supportive to hypothesis 4, firms with high idiosyncratic risks have higher sensitivity to economic policy uncertainty and they are subject to a higher analyst forecast compared with firms with low idiosyncratic risks. These results are aligned with the results in panels A1 and A2 of Table 5 as small start-up firms are considered risky firms in general, and we can see that both EPU-sensitivity and analyst forecast errors are high for small firms as well as firms with high idiosyncratic risk.

I further my test to check on whether idiosyncratic risk increases with EPU and report the results in panel C of table 8. Intent of this test is to find whether EPU increases idiosyncratic risk, and that increases the firm-level EPU-sensitivity in turn. However, I find no evidence of positive relation between EPU and idiosyncratic risk. This is suggestive of no or little effect of EPU on idiosyncratic risk.

4.6 Progressive Effect of Economic Policy Uncertainty

Gulen and Ion (2016) show that the effect of EPU on investment levels remains up to five quarters, and EPU induces significant fluctuations in investments for up to six years into the future. This implies that, after high uncertainty resolves, firm activities become normal over time as the effect of EPU reduces over time. This brings up the possibility of long-term effect of EPU on forecast error. Following Gulen and Ion (2016), I explore how long EPU affects the analyst forecast errors. Using the baseline model in equation 1, I run the regressions in iterations by increasing the time difference between the analyst forecast error and the economic policy uncertainty by 1 month in each iteration. Initially, I run six iterations and report the results in Table 9. Here, the effect of the economic policy uncertainty on the analyst forecast is positive and significant for all the six regressions. To have a closer look on this, I run the regressions in another 24 iterations. From the results, I find that the effect of economic policy uncertainty on analyst forecast error is positive and significant for 13 months and positive but insignificant for another five months. After 18 months, the effect of EPU becomes negative. I present the results of the first 24 regressions graphically in figure 2 where it can be observed that the effect of EPU on analyst forecast errors decrease gradually over time. Overall, results establish that the economic policy uncertainty can affect the future analyst forecast errors adversely for more than one year. This effect decreases over time as the time difference between the high EPU and earnings forecast increases. These results are aligned with the idea that, when the uncertainty resolves, financial markets do not recover instantly but gradually. Analyst forecast errors decrease over time and along with the decrease in uncertainty about firms' performance. This result is also conforming to inverse Oi-Hartman-Abel effect in the short run and to Oi-Hartman-Abel effect in the long run as we can see the negative effect of EPU in the beginning, decreasing magnitude and significance of uncertainty over time, and positive effect of EPU in the long run.

4.7 Alternate Macroeconomic Controls

Though the regression results in Tables 2 and 3 show a positive and significant effect of EPU on the analyst forecast errors, there is a possibility that the EPU measure is capturing some general economic condition or uncertainty at the macro level. Studies have shown that the economic policy uncertainty is countercyclic (Bloom, 2014; Gulen & Ion, 2016; Nguyen & Phan, 2017; Brogaard & Detzel, 2015). Some exogenous shocks can worsen the economy and increase the general uncertainty at the same time. Bloom (2014) argues that, when the economic condition is good, firms and individuals trade and invest actively, information on the firms flows normally, and policymakers become less likely to change the monetary policy or fiscal policy. These dynamics create lower uncertainties in both macro and micro levels. On the other hand, when the general economic condition is bad, firms become less active in their trading and investments causing limited information generation, and the policy-makers become more likely to experiment with the monetary and fiscal policies to boost the economy. These dynamics create higher uncertainties in both macro and micro levels and difficulties in predicting firm performance as well as policy-makers' decisions. To investigate on whether economic policy uncertainty is arising from other cyclical economic indicators, I test with two sets of macroeconomic proxies for general economic conditions and economic uncertainty.

I begin the analysis on alternate macroeconomic variables with five macroeconomic proxies for general economic conditions. First, I use the real GDP data that represents present economic condition. Second, I use the forecasts for one-year ahead GDP growth rate from the Livingston survey of Philadelphia Federal Reserve that represents the prospective economy in the opinion of the economists. Third, I use the US leading index that includes several variables that lead the economy. Fourth, I use the Composite Leading Indicators (CLI) that is built upon several economic components and designed to show fluctuation of the economic activity around its long-term potential level. Last, I use the Financial Stress index that is designed to monitor financial market developments and can be used by regulators to engage in financial market monitoring.

Next, I use four macroeconomic proxies for economic uncertainty. First, I use the dispersion in forecasts for GDP growth rate that represents the uncertainty in future economic growth. Second, I use VXO, a common measure of investors' uncertainty. To gauge the perceived uncertainty in the equity market, I use the monthly cross-sectional standard deviation of stock returns as the third proxy. Finally, I use the aggregate uncertainty measure JLN (Jurado, Ludvigson, & Ng, 2015) as an alternate measure of economic uncertainty.

I add each of these proxies separately to the baseline model first and then I add all the macroeconomic proxies together and run the regressions. Results of the regressions with general economic condition variables, economic uncertainty variables, and all variables together are reported in the panels A, B, and C, respectively, of Table 10. Results show that EPU remains a positive and significant determinant of the analyst forecast errors in all the regressions. Although the economic and statistical significances of the effect decrease a little (compared with the results in panel A of Table 2) when all variables are used together, this is not surprising considering overlap of some macroeconomic conditions that are included in these measures. Specification 9 regression results imply that a doubling of EPU affects the analyst forecast error by 1.81 percentage points after controlling for various macroeconomic proxies.

4.8 Business Cycle Interactions

Business cycle phases change in conjunction with the economic condition, and the economic agents' activities (trading, investment, etc.) differ in different phases of business cycles. When the economic condition is poor, economic uncertainty as well as economic policy uncertainty increase. During high uncertainty, investors are more likely to invest in risk-free assets and demand higher risk premiums for risky assets. The high demand of risk-free assets lowers the risk-free rate and the demand for higher risk premiums increases the rates for the risky or long-term assets. These dynamics increase the yield spreads between the risky and risk-free assets and the spreads between the long-term and short-term assets. Thus, during poor economic conditions, the default spread (DEF), term spread (TERM), and dividend yield (DIV) increase along with the increase in the uncertainty, and the risk-free rate (TB) decreases. Panels A, B, and D of figure 3 show that the countercyclic business cycles default spread (DEF), term spread (TERM), and dividend yield (DIV) have trends similar to that of EPU. Panel C of figure 3 shows that the high levels of EPU and low levels of risk-free rate (and vice versa) coexist most of the times. Both the EPU and the business cycles are related to the general economic condition, and so, business cycles may have some explanatory power of the economic policy uncertainty. Although business cycles do not explain the EPU fully (Brogaard & Detzel, 2015), EPU may have different degrees of impacts on the analyst forecast errors during different phases of business cycles. So, in this section of the study, I examine the interaction effect of business cycles with the EPU on the analyst forecast errors. [Appendix C contains details on the business cycles.] Results are available with me and not reported here in this paper.

I begin with the financial business cycles and add the interaction terms to the baseline model. The interactions of EPU with the financial business cycles DEF, TERM, and DIV are found to be positive and significant. This means that higher the magnitudes of DEF, TERM, and DIV, higher is the effect of EPU on the analyst forecast errors. The interaction of EPU with the financial business cycle TB is found to be negative and significant. This means that lower the magnitude of TB, higher is the effect of EPU on the analyst forecast errors. The coefficient of the interaction term $EPU \times TB$ is negative because the EPU is countercyclic whereas the TB is procyclic.

During the poor economic conditions, inflation rate lowers, unemployment rate increases, and industrial production growth lowers. These macroeconomic business cycles along with the EPU are presented graphically in the panels A through C of figure 4. To investigate the interaction effects of macroeconomic business cycles empirically, I add the interaction terms for three macroeconomic business cycles – inflation rate, unemployment rate, and industrial production growth – to the baseline model. Results show a positive and significant interaction term $EPU \times Unemployment$ signifying that the effect of EPU on the analyst forecast errors increases as the unemployment rate increases. A negative and significant interaction term $EPU \times IP\ Growth$ denotes that the effect of EPU on the analyst forecast errors decreases as the industrial production growth increases. An insignificant interaction term $EPU \times Inflation$ might be because the EPU index captures the inflation component.

Finally, I check the effect of EPU on the analyst forecast errors during contractions and expansions. Here I use the NBER recession indicators that denote the trough (recession) and peak time periods. First, I run regressions conditional on recession dummy = 0 (peak) and recession dummy = 1 (trough). In both the cases, EPU has a positive and significant effect on the analyst forecast errors with a higher effect during the trough. Results show that, when high EPU and recession coexists, a doubling of the EPU may affect the analyst forecast errors by as high as 19.73 percentage points.

4.9 Endogeneity Check

A general concern with the EPU index is that it may capture economic uncertainty that is not related to the economic policy. In that case, the regression results may suffer from measurement error bias. Although Baker, Bloom, and Davis (2016) have taken actions to minimize this possibility, here I seek to alleviate this concern further by exploiting the close tie between the USA and Canadian economies.

As a result of free-trade agreements among North American countries, the USA and Canada economies are tightly linked through the extensive trade activities between these two countries (Romalis, 2007). Gulen and Ion (2016) assert that a shock in one economy is likely to affect the other economy. If USA EPU index captures some non-policy related economic factors, those factors will be present in Canadian EPU index as well. This means that, if the USA EPU is regressed on the Canadian EPU, non-policy related economic factors common to both the economies will be absorbed, and the residual should constitute a cleaner form of the economic policy uncertainty in the USA. Following Gulen and Ion (2016) and Nguyen and Phan (2017), I run the two-stage regression using Canadian EPU as an instrument, and find that the instrumented EPU has a positive and significant effect although its significance is weakened (results are available with me, but not reported to save space). The results of the Kleibergen-Paap underidentification test and Cragg-Donald Wald weak identification test also show that the instrument is relevant.[12] The results indicate that the findings of this study are robust to endogeneity correction.

5 Concluding Remarks

This study provides evidence that the economic policy uncertainty has a negative effect on the analyst forecast accuracy, and this effect persists for 13 months in the future. The viable reason behind a negative of EPU is that the analysts (as outsiders) cannot anticipate the exact effect of EPU on the firms' performances and earnings when the EPU becomes high. As financial market activities and firms' performances become normal over time, and uncertainty about those reduces gradually after high EPU dissolves, analyst forecast accuracy does not improve

[12] I could not test for overidentification as the model is just identified.

immediately after the EPU level lowers. Thus, we can see the effect of EPU on analyst forecast errors to persist for a few months, and during this period, effect of EPU reduces and accuracy of analyst forecast error improves.

Results show that the forecast errors are higher for the firms that have higher sensitivity to uncertainty. Volatility and dispersion in analyst forecast errors increase during periods of high EPU because uncertainty causes higher divergence in analysts' opinions about firm performance. Both smaller firms and firms with high idiosyncratic risk are found to have higher sensitivity to the uncertainty and those firms are subject to higher forecast errors. This is suggestive of a considerable overlap between the smaller firms and firms with high idiosyncratic risk in my sample.

Overall, the study suggests the possibility of higher number (and amount) of suboptimal investments due to higher earnings forecast errors during the periods of high EPU. However, this study brings forth some open questions related to the context of this study. Do the stock market investors discount analysts' recommendations during the periods of high EPU? Does the frequency of analyst recommendations become less during periods of high uncertainty? To what extent are the investors affected due to the increase in earnings forecast errors? Is the bias (sign) of average forecast error during high EPU different from that during low EPU? If different, how much? Does the difference between one and five quarter ahead forecasts increase during periods of high uncertainty?

The study results synchronize with the economic policy uncertainty literature that shows various negative effects of EPU. This study is also aligned with the analyst forecast literature that shows factors and situations affecting analyst forecast accuracy. While the study shows the evidence of negative effect of EPU on analyst forecast errors and a channel through which EPU affects forecast error, causaliy of EPU is not clear yet. As suggested by Baker, Bloom, and Davis (2016), further investigations on this is required to clarify the causality of EPU.

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Figure 1: Economic Policy Uncertainty Index

The figure below shows the graphical presentation of the economic policy uncertainty (EPU) index along with NBER recession indicators over the sample period of January 1994 to December 2015. EPU index, a proxy of aggregate uncertainty related to economic policies, is developed by Baker, Bloom, and Davis (2016).

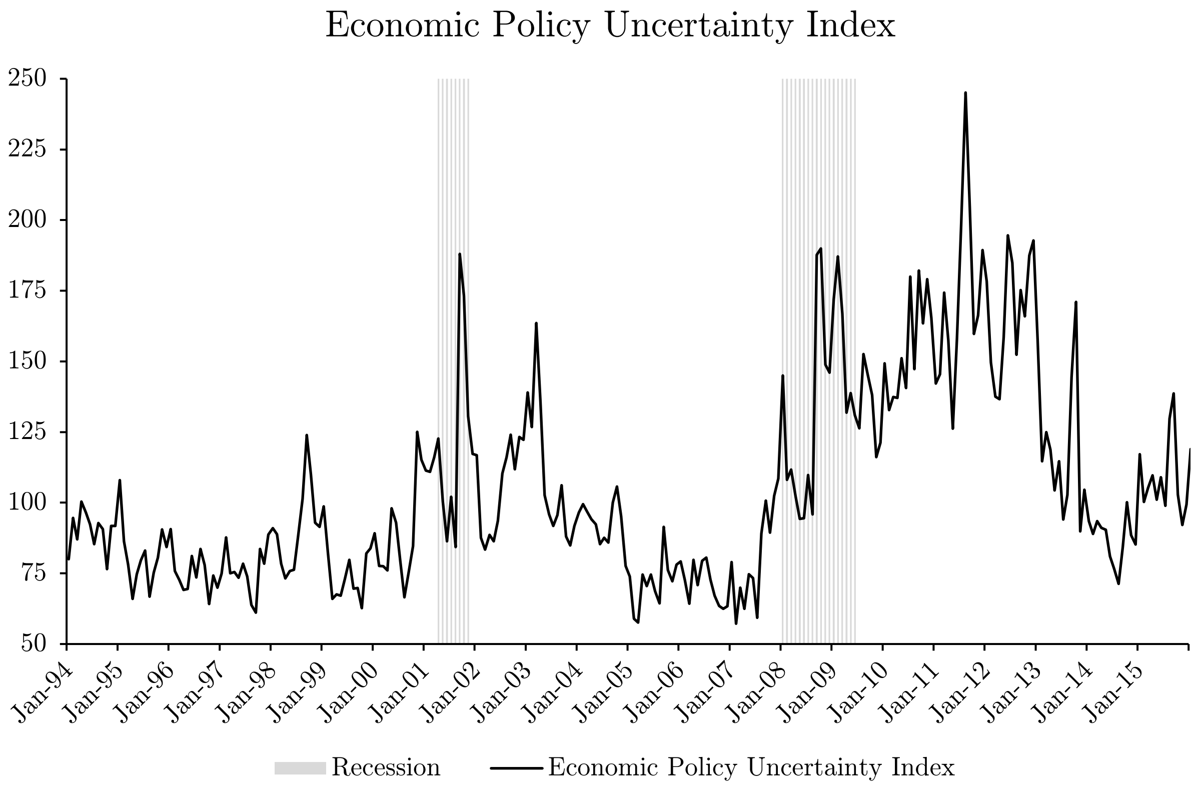

Figure 2: The Effect of EPU on Analyst Forecast Errors over Time

This figure shows the effect of EPU on analyst forecast error in percentage points over the period of 24 months. Analyst forecast errors are regressed on the lagged EPU starting from EPU at 1-month lag up to EPU at 24-month lag with respect to analyst forecast. All regressions use the baseline model (equation 1) and include the control variables average stock returns over past 12 months, book-to-market value of equity, leverage, change in earnings, and earnings standard deviation. Monthly data span from Jan 1994 to Dec 2015. All specifications include the analyst forecast error as the dependent variable, one period lagged independent variables, firm fixed effects, and clustering of standard errors. All variables are standardized using their sample means and standard deviations.

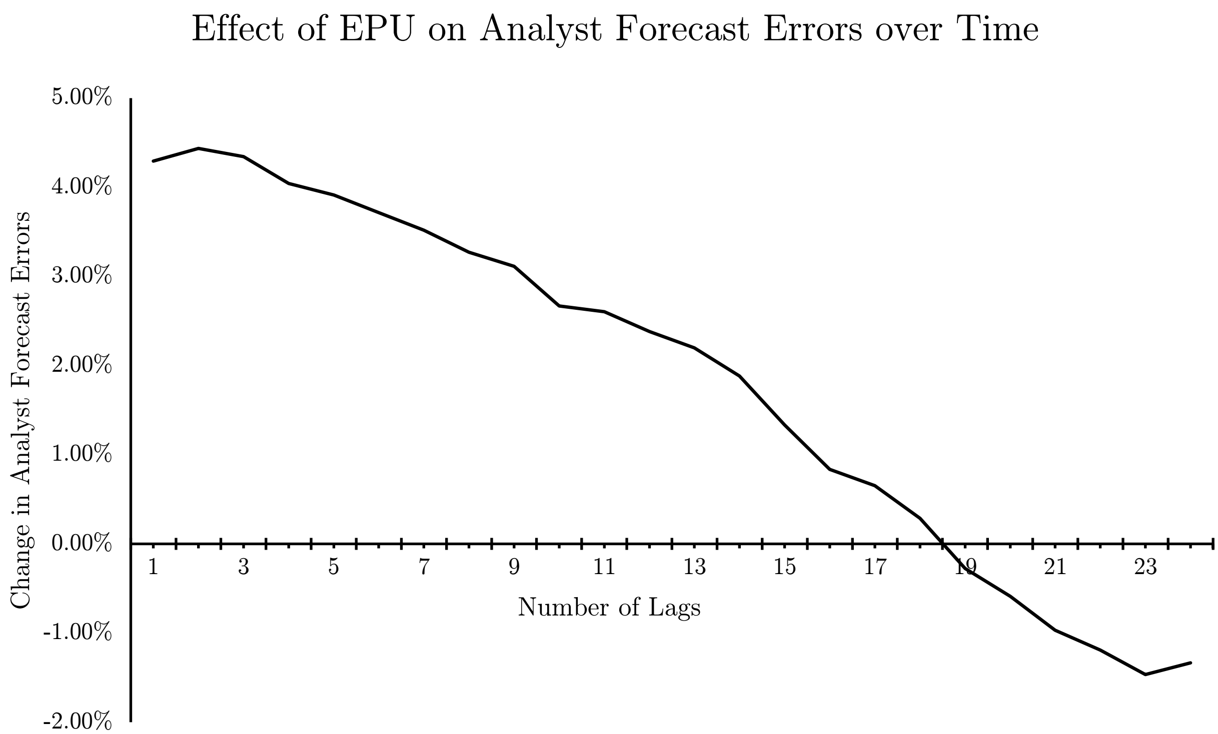

Figure 3: EPU and Financial Business Cycles

The figure below shows the economic policy uncertainty (EPU) with four financial business cycles over the sample period of January 1994 to December 2015 in the four panels below. In all the panels, EPU scale is on the major axis (at the left side) and business cycle scales are on the minor axis (at the right side). Financial business cycles in the panels A through D are default spread, TERM spread, 1-month Treasury Bill rate, and Dividend Yield, respectively. All variables are defined in Appendix C1.

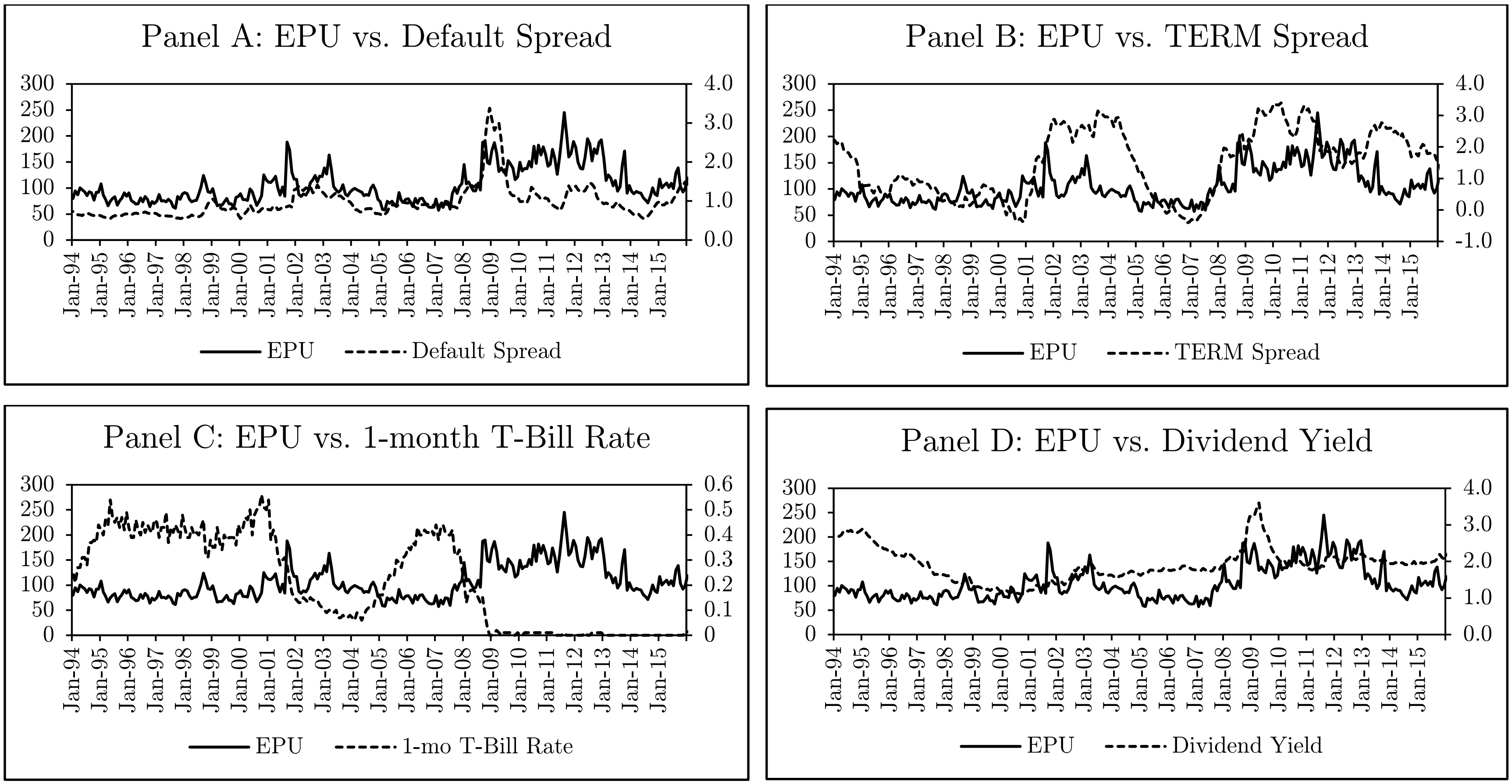

Figure 4: EPU and Macroeconomic Business Cycles

The figure below shows the economic policy uncertainty (EPU) with three macroeconomic business cycles over the sample period of January 1994 to December 2015 in the three panels below. In all the panels, EPU scale is on the major axis (at the left side) and business cycle scales are on the minor axis (at the right side). Macroeconomic business cycles in the panels A through C are inflation rate, industrial production growth rate, and unemployment rate, respectively. All variables are defined in Appendix C2.

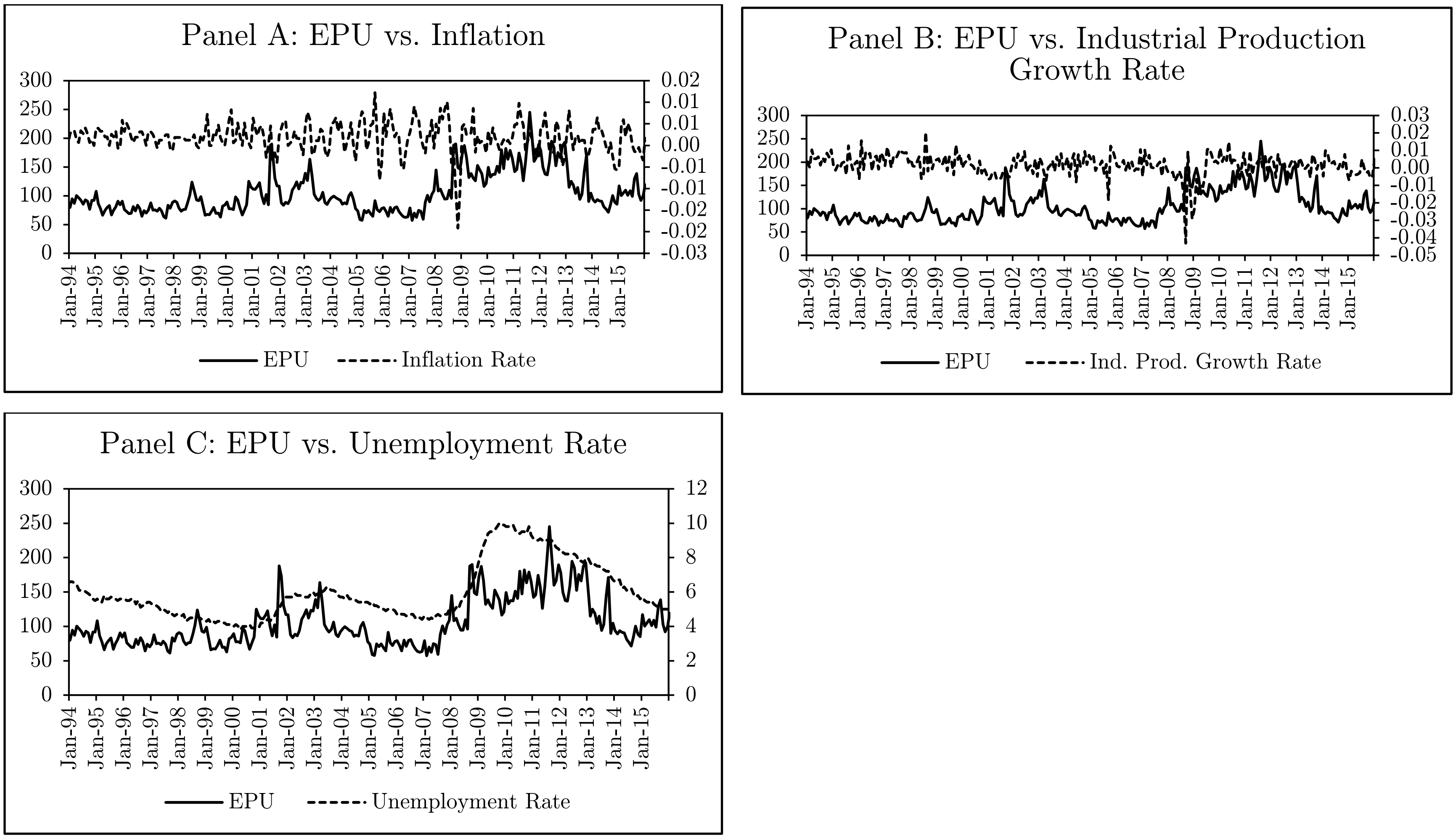

Table 1: Summary Statistics

Panel A presents the descriptive statistics of the main variables used in the study. Variables included in the table are the analyst forecast error in percentage, economic policy uncertainty (EPU) index from Baker, Bloom, and Davis (2016), monthly changes in the EPU, monthly stock returns, book-to-market value of equity (BE/ME), leverage, change in earnings (ΔEarnings), and earnings standard deviation (Earnings SD). Panel B presents the correlations between the EPU index, Canada economic policy uncertainty index, real GDP, forecast for GDP growth rate (forecast for ΔGDP), Leading Index for the United States, Composite Leading Indicator, dispersion in forecasts for GDP growth rate, financial stress index, implied volatility index VXO of CBOE, monthly cross-sectional standard deviation of stock returns, and JLN uncertainty measure. Frequency of real GDP data is quarterly. Frequency of forecast for GDP growth rate and dispersion in forecasts for GDP growth rate are semi-annual. All other variables are obtained at monthly level. Data used here span from January 1994 to December 2015. Variables in the panel A and panel B are defined in the Appendix A and Appendix B, respectively.

Panel A: Descriptive Statistics of the Main Variables

	N	Mean	Min	Max	SD	P25	P50	P75
Forecast Error	415900	29.0489	0.0000	350.0000	46.7546	4.6296	11.9178	30.7692
EPU	415900	103.6903	57.2026	245.1267	35.7301	77.5483	91.7370	123.2844
Change in EPU	415900	12.8906	0.0197	103.7704	13.1698	4.4822	9.5155	16.1599
Return	415900	0.0049	−0.6813	3.2864	0.0476	−0.0145	0.0074	0.0264
BE/ME	415900	0.5849	−1.2756	4.5049	0.5847	0.2873	0.4945	0.7820
Leverage	415900	0.2436	0.0000	0.9155	0.2334	0.0345	0.1828	0.3921
ΔEarnings	415900	1.2794	0.0000	17.8000	2.8177	0.1591	0.3871	1.0071
Earnings SD	415900	1.7004	0.0000	21.2390	3.5254	0.2650	0.5220	1.3696

Panel B: Correlation matrix

	EPU	EPU Canada	GDP	ΔGDP	USLI	CLI	Disp.	Fin. Stress	VXO	σ(Ret)	JLN
Policy Uncertainty Overall (EPU)	1										
Policy Uncertainty - Canada	0.62	1									
Real GDP (GDP)	0.43	0.20	1								
Forecast for ΔGDP	−0.35	−0.33	−0.21	1							
Leading Index for the US (USLI)	−0.37	−0.14	−0.27	0.48	1						
Composite Leading Indicator (CLI)	−0.45	−0.39	0.05	0.53	0.72	1					
Dispersion in ΔGDP forecast (Disp.)	0.40	0.28	0.17	−0.60	−0.42	−0.47	1				
Financial Stress Index (Fin. Stress)	−0.02	−0.04	−0.51	−0.12	−0.53	−0.49	0.17	1			
VXO	0.40	0.23	−0.04	−0.27	−0.56	−0.56	0.14	0.66	1		
Return Std. Dev. (σ(Ret))	−0.04	−0.10	−0.36	0.00	−0.31	−0.40	0.00	0.62	0.47	1	
JLN measure	0.33	0.03	0.28	−0.28	−0.86	−0.53	0.34	0.61	0.59	0.35	1

Table 2: Effect of EPU on Analyst Forecast Accuracy

This table reports regressions of analyst forecast error on the economic policy uncertainty (EPU) index with control variables that include average stock returns over past 12 months (Return), book-to-market value of equity (BE/ME), leverage, change in earnings (ΔEarnings), and earnings standard deviation (Earnings SD). Panels A shows regressions on EPU index level, monthly changes in EPU index, and log of EPU index that are marked as specification (1) through (3), respectively. All variables are defined in Appendix A. Panel B shows regressions on the four components of EPU index – news, government spending, inflation, and tax – that are marked as specification (1) through (4), respectively. Monthly data used here span from January 1994 to December 2015. All specifications include the analyst forecast error as the dependent variable, one period lagged independent variables, fixed effects, and clustering of standard errors. All variables are standardized using their sample mean and standard deviation. The t-statistics are reported in parentheses. The statistical significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Panel A: Overall Economic Policy Uncertainty Index				
	Expected Signs	(1)	(2)	(3)
EPU level	+	0.0311**		
		(2.59)		
Change in EPU	+		0.0128*	
			(2.07)	
Log of EPU	+			0.0328***
				(2.85)
Return	–	−0.0618***	−0.0631***	−0.0617***
		(−6.23)	(−5.75)	(−6.26)
BE/ME	+	0.0387***	0.0440***	0.0384***
		(3.75)	(3.70)	(3.79)
Leverage	+	0.1757***	0.1792***	0.1752***
		(14.59)	(14.33)	(14.63)
ΔEarnings	+	0.0468***	0.0474***	0.0467***
		(9.27)	(9.39)	(9.25)
Earnings SD	+	0.0543***	0.0554***	0.0542***
		(13.87)	(13.92)	(13.78)
N		415,900	415,900	415,900
R-squared		0.222	0.221	0.222
Firm fixed effects		Yes	Yes	Yes
Month Dummies		Yes	Yes	Yes
Cluster by firm		Yes	Yes	Yes
Cluster by year		Yes	Yes	Yes

(*Continued*)

Panel B: Effects of Individual EPU Components				
	(1)	(2)	(3)	(4)
EPU News Component	0.0204**			
	(2.41)			
EPU Govt. Component		0.0222		
		(1.70)		
EPU CPI Component			0.0326***	
			(3.01)	
EPU Tax Component				0.0431***
				(3.48)
Return	−0.0619***	−0.0644***	−0.0628***	−0.0645***
	(−5.91)	(−6.01)	(−6.19)	(−6.48)
BE/ME	0.0416***	0.0399***	0.0413***	0.0399***
	(3.70)	(4.38)	(4.10)	(3.88)
Leverage	0.1772***	0.1779***	0.1774***	0.1765***
	(14.34)	(14.39)	(14.66)	(14.69)
ΔEarnings	0.0470***	0.0475***	0.0467***	0.0468***
	(9.36)	(9.04)	(9.63)	(9.18)
Earnings SD	0.0550***	0.0552***	0.0548***	0.0534***
	(13.86)	(13.67)	(13.96)	(13.86)
N	415,900	415,900	415,900	415,900
R-squared	0.221	0.221	0.222	0.222
Firm fixed effects	Yes	Yes	Yes	Yes
Month Dummies	Yes	Yes	Yes	Yes
Cluster by firm	Yes	Yes	Yes	Yes
Cluster by year	Yes	Yes	Yes	Yes

Table 3: Firm-Level EPU-Sensitivity

This table reports results on effect of firm-level sensitivity to EPU on analyst forecast error. First, the firm-level excess return is regressed on monthly changes in EPU and Fama-French 3-factors or 5-factors in 60-month rolling window to obtain the monthly firm-level sensitivity to EPU. Next, the firm-level sensitivity to EPU is used as the independent variable in the second regression. Panels A and B use sensitivity to EPU obtained using Fama-French 3-factors and 5-factors, respectively. Details on the methodology are documented in section 3.2.2. Monthly data used here span from January 1994 to December 2015. All specifications include the analyst forecast error as the dependent variable, one period lagged independent variables, control variables, fixed effects, and clustering of standard errors. Control variables include average stock returns over past 12 months (Return), book-to-market value of equity (BE/ME), leverage, change in earnings (ΔEarnings), and earnings standard deviation (Earnings SD). Appendix A contains details on these variables. All variables are standardized using their sample mean and standard deviation. Specifications marked (1) through (4) show results using different sets of fixed effects. The t-statistics are reported in parentheses. The statistical significance at the 0.1%, 1%, 5%, and 10% levels are indicated by ***, **, *, and +, respectively.

Panel A: Sensitivity to EPU using Fama-French 3-factors				
	(1)	(2)	(3)	(4)
Sensitivity to EPU	0.0025***	0.0023***	0.0022***	0.0037***
	(6.12)	(9.25)	(13.82)	(3.98)
Return	−0.0491***	−0.0485***	−0.0454***	−0.0709***
	(−4.78)	(−5.01)	(−4.76)	(−5.93)
BE/ME	0.0372*	0.0309*	0.0328**	0.0293
	(2.57)	(2.44)	(3.18)	(1.50)
Leverage	0.1899***	0.1897***	0.1518***	0.1336***
	(12.76)	(14.29)	(12.26)	(12.45)
ΔEarnings	0.0682***	0.0639***	0.0521***	0.0934***
	(15.28)	(14.34)	(12.11)	(15.46)
Earnings SD	0.0587***	0.0532***	0.0418***	0.0812***
	(9.37)	(9.28)	(7.85)	(15.21)
N	1,490,961	1,490,961	1,490,961	1,490,961
R-squared	0.239	0.256	0.314	0.164
Firm fixed effects	Yes	Yes	Yes	No
Year fixed effects	Yes	Yes	No	Yes
Industry fixed effects	No	No	No	Yes
Analyst fixed effects	No	Yes	Yes	Yes
Industry-Year fixed effects	No	No	Yes	No
Cluster by year	Yes	Yes	Yes	Yes
Cluster by firm	Yes	Yes	Yes	Yes

(*Continued*)

Panel B: Sensitivity to EPU using Fama-French 5-factors				
	(1)	(2)	(3)	(4)
Sensitivity to EPU	0.0027***	0.0025***	0.0022***	0.0039**
	(4.72)	(6.36)	(11.31)	(3.75)
Return	−0.0491***	−0.0485***	−0.0454***	−0.0709***
	(−4.78)	(−5.01)	(−4.76)	(−5.93)
BE/ME	0.0372*	0.0309*	0.0328**	0.0293
	(2.57)	(2.44)	(3.18)	(1.50)
Leverage	0.1899***	0.1897***	0.1518***	0.1336***
	(12.76)	(14.29)	(12.26)	(12.45)
ΔEarnings	0.0682***	0.0639***	0.0521***	0.0934***
	(15.28)	(14.34)	(12.11)	(15.46)
Earnings SD	0.0587***	0.0532***	0.0418***	0.0812***
	(9.37)	(9.28)	(7.85)	(15.21)
N	1,490,961	1,490,961	1,490,961	1,490,961
R-squared	0.239	0.256	0.314	0.164
Firm fixed effects	Yes	Yes	Yes	No
Year fixed effects	Yes	Yes	No	Yes
Industry fixed effects	No	No	No	Yes
Analyst fixed effects	No	Yes	Yes	Yes
Industry-Year fixed effects	No	No	Yes	No
Cluster by year	Yes	Yes	Yes	Yes
Cluster by firm	Yes	Yes	Yes	Yes

(*Continued*)

Panel C: Control by and Interaction with risk factors of Fama-French 3-factor model

Panel C1: Market Excess Return			
	(1)	(2)	(3)
Sensitivity to EPU	0.0025***	0.0025***	0.0024***
	(6.30)	(6.41)	(8.23)
EPU × Market Excess Return	-0.0094+	0.0006	
	(-1.84)	(1.56)	
Market Excess Return	0.0143+		0.0059
	(1.77)		(1.64)
Controls	Yes	Yes	Yes

Panel C2: Small-minus-big			
	(1)	(2)	(3)
Sensitivity to EPU	0.0025***	0.0025***	0.0024***
	(6.58)	(6.36)	(7.87)
EPU × SMB	-0.0266*	0.0008***	
	(-2.44)	(6.15)	
SMB	0.0342*		0.0066
	(2.49)		(1.26)
Controls	Yes	Yes	Yes

Panel C3: High-minus-low			
	(1)	(2)	(3)
Sensitivity to EPU	0.0025***	0.0025***	0.0023***
	(7.05)	(6.16)	(9.92)
EPU × HML	-0.0076***	0.0002	
	(-4.19)	(0.52)	
HML	0.0315***		0.0284***
	(4.32)		(4.11)
Controls	Yes	Yes	Yes

(*Continued*)

Panel D: Control by and Interaction with risk factors of Fama-French 5-factor model			
Panel D1: Market Excess Return			
	(1)	(2)	(3)
Sensitivity to EPU	0.0026***	0.0026***	0.0026***
	(4.94)	(4.94)	(5.27)
EPU × Market Excess Return	-0.0037	0.0005	
	(-0.60)	(1.01)	
Market Excess Return	0.0049		0.0015
	(0.68)		(0.79)
Controls	Yes	Yes	Yes
Panel D2: Small-minus-big			
	(1)	(2)	(3)
Sensitivity to EPU	0.0025***	0.0025***	0.0024***
	(7.38)	(6.50)	(7.94)
EPU × SMB	-0.0084	0.0024***	
	(-0.96)	(25.77)	
SMB	0.0118		0.0036**
	(1.22)		(3.09)
Controls	Yes	Yes	Yes
Panel D3: High-minus-low			
	(1)	(2)	(3)
Sensitivity to EPU	0.0025***	0.0025***	0.0024***
	(6.88)	(6.56)	(7.55)
EPU × HML	-0.0072	0.0021**	
	(-0.88)	(3.03)	
HML	0.0102		0.0034
	(1.06)		(1.67)
Controls	Yes	Yes	Yes
Panel D4: Robust-minus-weak			
	(1)	(2)	(3)
Sensitivity to EPU	0.0026***	0.0026***	0.0025***
	(4.88)	(5.40)	(6.11)
EPU × RMW	-0.0074	0.0011	
	(-0.93)	(0.98)	
RMW	0.0097		0.0029
	(1.15)		(1.22)
Controls	Yes	Yes	Yes
Panel D5: Conservative-minus-aggressive			
	(1)	(2)	(3)
Sensitivity to EPU	0.0027***	0.0027***	0.0027***
	(4.83)	(4.75)	(5.07)
EPU × CMA	-0.0053+	0.0008	
	(-2.06)	(0.56)	
CMA	0.0168**		0.0142**
	(3.17)		(3.26)
Controls	Yes	Yes	Yes

Table 4: Industry-Level Heterogeneity

This table presents the effect of EPU on the analyst forecast error at the industry level. Panel A reports the regression result at the industry level using Fama-French 12 industry groups. Panel B reports the effect of interaction between EPU and industry level government spending on the analyst forecast error. All variables are defined in Appendix A. Monthly data used here span from January 1994 to December 2015. All specifications include analyst the forecast error as the dependent variable, one period lagged independent variables, control variables, fixed effects, and clustering of standard errors. All variables are standardized using their sample mean and standard deviation. The t-statistics are reported in parentheses. The statistical significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Panel A: Industry Level Regressions

	(1) Nondurables	(2) Durables	(3) Manuf.	(4) Energy	(5) Chemicals	(6) Bus. Equip.
EPU	0.0620	−0.2192**	0.9858**	0.4119*	2.8987***	0.0027***
	(0.13)	(−2.60)	(2.27)	(1.85)	(5.33)	(12.56)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	64,257	26,922	139,665	113,749	39,741	257,311
R-squared	0.226	0.276	0.217	0.147	0.248	0.145
Analyst fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by firm	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by year	Yes	Yes	Yes	Yes	Yes	Yes

	(7) Telecom.	(8) Utilities	(9) Shops	(10) Healthcare	(11) Finance	(12) Other
EPU	0.0275	0.1533	0.7999***	0.1394	0.2050	0.2422
	(0.05)	(0.19)	(3.47)	(1.24)	(1.01)	(1.33)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	37,114	37,652	178,987	118,246	228,068	249,249
R-squared	0.222	0.105	0.206	0.164	0.248	0.218
Analyst fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by firm	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by year	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Firm Size and Capital Structure

This table reports the univariate statistics of analyst forecast error and firm-level EPU-sensitivity. Panels A1 and A2 present the EPU-sensitivity statistics and analyst forecast error statistics, respectively, in firm size quintiles. Panels B1 and B2 present the EPU-sensitivity statistics and analyst forecast error statistics, respectively, in debt-to-equity ratio quintiles. All variables are defined in Appendix A. In each panel, Hi − Lo column shows the difference between the statistics in quintile 5 and quintile 1 for each statistical measure. Dispersion is measured as the difference between the 75th percentile and the 25th percentile of EPU-sensitivity statistics in each quintile. The Data used here span from January 1994 to December 2015.

Panel A1: EPU-Sensitivity Univariate Statistics in Firm Size Quintiles

Sensitivity to EPU	Firm Size Quintiles					Hi − Lo
	1	2	3	4	5	
Mean	0.0028	0.0020	0.0018	0.0016	0.0015	−0.0013
Std. Dev	0.1392	0.0041	0.0027	0.0027	0.0013	−0.1379
P25	0.0008	0.0007	0.0006	0.0005	0.0004	−0.0004
P50	0.0018	0.0015	0.0013	0.0012	0.0011	−0.0007
P75	0.0033	0.0028	0.0025	0.0025	0.0023	−0.0011
Dispersion	0.0025	0.0022	0.0020	0.0020	0.0019	−0.0007

Panel A2: Analyst Forecast Error Univariate Statistics in Firm Size Quintiles

Sensitivity to EPU	Firm Size Quintiles					Hi − Lo
	1	2	3	4	5	
Mean	21.2006	17.6944	16.2526	15.3870	12.9068	−8.2938
Std. Dev	21.9114	19.8992	19.0972	18.6971	16.5655	−5.3459
P25	4.8387	3.8462	3.4483	3.0942	2.5974	−2.2413
P50	13.5593	10.5263	9.0909	8.3333	6.8966	−6.6628
P75	31.2500	24.1379	21.4286	20.0000	16.1290	−15.1210
Dispersion	26.4113	20.2918	17.9803	16.9058	13.5316	−12.8797

Panel B1: EPU-Sensitivity Univariate Statistics in Debt-to-Equity Ratio Quintiles

Sensitivity to EPU	Debt-to-Equity Ratio Quintiles					Hi − Lo
	1	2	3	4	5	
Mean	0.0025	0.0018	0.0017	0.0018	0.0019	−0.0006
Std. Dev	0.1405	0.0038	0.0020	0.0028	0.0036	−0.1368
P25	0.0007	0.0005	0.0005	0.0006	0.0006	−0.0001
P50	0.0016	0.0014	0.0013	0.0013	0.0014	−0.0002
P75	0.0030	0.0026	0.0026	0.0026	0.0027	−0.0003
Dispersion	0.0023	0.0021	0.0021	0.0020	0.0021	−0.0002

Panel B2: Analyst Forecast Error Univariate Statistics in Debt-to-Equity Ratio Quintiles

Sensitivity to EPU	Debt-to-Equity Ratio Quintiles					Hi − Lo
	1	2	3	4	5	
Mean	17.1083	13.5907	14.5831	17.2096	20.9511	3.8428
Std. Dev	19.3065	16.8588	17.5768	19.5815	22.8120	3.5055
P25	3.7736	2.8571	3.0303	3.7037	4.1096	0.3360
P50	10.1266	7.5000	8.1967	10.0000	12.1622	2.0356
P75	23.3333	17.1429	19.0000	23.3333	30.0000	6.6667
Dispersion	19.5597	14.2857	15.9697	19.6296	25.8904	6.3307

Table 6: Seasonality in earnings forecast errors

This table reports regressions using base specification for the three months in the quarters separately. Specifications marked (1) through (3) use the first month through third month of the calendar-quarters, respectively. All variables are defined in Appendix A. Monthly data used here span from January 1994 to December 2015. All specifications include analyst the forecast error as the dependent variable, one period lagged independent variables, control variables, fixed effects, and clustering of standard errors as specified in equation 1. All variables are standardized using their sample mean and standard deviation. The t-statistics are reported in parentheses. The statistical significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)
	Quarter-month 1	Quarter-month 2	Quarter-month 3
EPU	0.0322**	0.0321***	0.0334**
	(2.61)	(2.94)	(2.82)
Controls	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Cluster by firm	Yes	Yes	Yes
Cluster by year	Yes	Yes	Yes

Table 7: Volatility and Dispersion in Earnings Forecast Errors

This table presents the univariate statistics of analyst forecast error in EPU quintiles. Dispersion is measured as the difference between the 75[th] percentile and the 25[th] percentile of the forecast errors within each quintile. Hi-Lo is the difference between the fifth quintile and the first quintile of the forecast errors for each statistic. Data used here span from January 1994 to December 2015. Total number of observations is 415,900. The statistical significance at the 0.1% level is indicated by ***.

Univariate Statistics of Analyst Forecast Error in EPU Quintiles						
Analyst Forecast Error	EPU Quintiles					Hi − Lo
	1	2	3	4	5	
Mean	26.04	26.39	28.94	31.63	33.54	7.50***
P25	4.00	3.94	4.54	5.06	6.30	2.30
P50	10.35	10.22	11.54	13.33	15.38	5.04
P75	26.47	26.67	30.00	34.29	37.89	11.42
Std. Dev.	44.06	45.14	47.45	48.96	48.65	4.59
Dispersion	22.47	22.72	25.46	29.22	31.60	9.13
N	101461	86159	80621	62674	84985	

Table 8: Idiosyncratic Risk

This table reports the univariate statistics of firm-level EPU-sensitivity, analyst forecast error, and idiosyncratic risk at different dimensions. All variables are defined in Appendix A. Panel A presents the EPU-sensitivity statistics in idiosyncratic risk quintiles, panel B presents the analyst forecast error in idiosyncratic risk quintiles, and panel C presents the idiosyncratic risk in EPU quintiles. Hi − Lo column shows the difference between the statistics in quintile 5 and quintile 1. The Data used here span from January 1994 to December 2015.

Panel A: EPU-Sensitivity Univariate Statistics in Idiosyncratic Risk Quintiles

Sensitivity to EPU	Idiosyncratic Risk Quintiles					Hi - Lo
	1	2	3	4	5	
Mean	0.0014	0.0017	0.0019	0.0022	0.0034	0.0020
Std. Dev.	0.0018	0.0030	0.0029	0.0039	0.2079	0.2061
P25	0.0004	0.0005	0.0006	0.0007	0.0008	0.0004
P50	0.0010	0.0013	0.0015	0.0016	0.0019	0.0009
P75	0.0023	0.0025	0.0027	0.0029	0.0037	0.0014

Panel B: Analyst Forecast Error Statistics in Idiosyncratic Risk Quintiles

Sensitivity to EPU	Idiosyncratic Risk Quintiles					Hi - Lo
	1	2	3	4	5	
Mean	11.0976	14.0620	17.2745	20.3050	25.2799	14.1822
Std. Dev.	14.3050	17.0937	19.5508	21.5003	24.5360	10.2310
P25	2.4390	3.0303	3.7615	4.5455	6.0000	3.5610
P50	6.1538	7.8947	10.0000	12.5000	16.6667	10.5128
P75	13.7931	18.0556	23.3645	29.0000	38.4615	24.6684

Panel C: Idiosyncratic Risk in EPU Quintiles

Idiosyncratic Risk	EPU Quintiles					Hi - Lo
	1	2	3	4	5	
Mean	0.0991	0.1048	0.1002	0.1131	0.1054	0.0064
Std. Dev.	0.0543	0.0595	0.0565	0.0672	0.0631	0.0088
P25	0.0592	0.0603	0.0578	0.0636	0.0596	0.0004
P50	0.0860	0.0899	0.0858	0.0963	0.0891	0.0032
P75	0.1266	0.1355	0.1307	0.1453	0.1354	0.0088

Table 9: Progressive Effect of EPU on Analyst Forecast Accuracy

This table reports regressions of analyst forecast error on the economic policy uncertainty (EPU) index from Baker, Bloom, and Davis (2016) with control variables that include average stock returns over past 12 months (Return), book-to-market value of equity (BE/ME), leverage, change in earnings (ΔEarnings), and earnings standard deviation (Earnings SD). All variables are defined in Appendix A. Time difference between forecast error and log transformed EPU is 1 to 6 for the specification marked (1) to (6), respectively. Monthly data used here span from January 1994 to December 2015. All specifications include the analyst forecast error as the dependent variable, lagged control variables, firm fixed effects, and clustering of standard errors. All variables are standardized using their sample mean and standard deviation. The t-statistics are reported in parentheses. The statistical significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1) Lag 1	(2) Lag 2	(3) Lag 3	(4) Lag 4	(5) Lag 5	(6) Lag 6
EPU	0.0328***	0.0332***	0.0323***	0.0292**	0.0278**	0.0267**
	(2.85)	(3.00)	(2.92)	(2.47)	(2.50)	(2.48)
Return	−0.0617***	−0.0642***	−0.0630***	−0.0630***	−0.0619***	−0.0589***
	(−6.26)	(−6.68)	(−6.90)	(−6.67)	(−6.95)	(−6.99)
BE/ME	0.0384***	0.0334***	0.0235**	0.0167*	0.0142	0.0072
	(3.79)	(3.29)	(2.28)	(1.75)	(1.54)	(0.82)
Leverage	0.1752***	0.1750***	0.1773***	0.1778***	0.1756***	0.1748***
	(14.63)	(15.11)	(15.63)	(15.80)	(15.46)	(15.50)
ΔEarnings	0.0467***	0.0397***	0.0364***	0.0336***	0.0304***	0.0278***
	(9.25)	(7.91)	(7.25)	(6.77)	(6.09)	(5.34)
Earnings SD	0.0542***	0.0520***	0.0488***	0.0462***	0.0421***	0.0391***
	(13.78)	(13.11)	(11.84)	(11.13)	(10.08)	(9.40)
N	415,900	413,509	411,358	408,990	406,395	404,490
R-squared	0.222	0.221	0.220	0.219	0.217	0.216
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by firm	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by year	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Alternate Macroeconomic Controls

This table presents results obtained from estimating the baseline model using several alternative macroeconomic proxies for general economic conditions (panel A), for economic uncertainty (panel B), and all economic variables together (panel C). The proxies for general economic conditions are the real GDP, the forecast for GDP growth rate (forecast for ΔGDP), the US Leading Index, the Composite Leading Indicators (CLI), and the financial stress indicator. The proxies for economic uncertainty are the dispersion in forecasts for GDP growth rate, the monthly VXO implied volatility index, the cross-sectional standard deviation in firm-level monthly stock returns, and the JLN uncertainty measure. Appendix B contains details on the macroeconomic variables. For brevity, I do not report the control variables. Monthly data used here span from January 1994 to December 2015. All specifications include the analyst forecast error as the dependent variable, one period lagged independent variables, firm fixed effects, and clustering of standard errors. All variables are standardized using their sample mean and standard deviation. The t-statistics are reported in parentheses. The statistical significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	Panel A: General economic condition					Panel B: Economic uncertainty				Panel C: All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
EPU	0.0257**	0.0232**	0.0168**	0.0184**	0.0316***	0.0229**	0.0286***	0.0325***	0.0212***	0.0138*
	(2.23)	(2.29)	(2.70)	(2.13)	(3.33)	(2.46)	(2.91)	(2.93)	(3.03)	(2.04)
Real GDP	0.0299***									0.0164
	(3.65)									(0.90)
Forecast for ΔGDP		−0.0286**								−0.0142*
		(−2.17)								(−2.03)
US Leading Index			−0.0501***							−0.0212*
			(−10.16)							(−1.73)
CLI				−0.0282*						−0.0019
				(−2.02)						(−0.19)
Financial Stress					0.0195					−0.0037
					(1.62)					(−0.19)
Dispersion						0.0258**				0.0038
						(2.10)				(0.65)
VXO							0.0096			−0.0166**
							(0.79)			(−2.34)
Return SD in C.S.								0.0060		−0.0022
								(0.49)		(−0.36)
JLN Measure									0.0474***	0.0371**
									(6.76)	(2.40)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix A: List of Variables

Compustat and CRSP variable names are in *Italicized* fonts and within parentheses.

Analyst forecast error: Absolute value of difference between actual and forecast EPS divided by the actual EPS as shown below.

$$FCE = abs\left(\frac{Actual - Forecast}{Actual}\right)$$

Book-to-Market Value of Equity (BE/ME): Book value of equity divided by the market value of equity. Book value of equity and market value of equity are calculated using data from annual Compustat and monthly CRSP, respectively.

Book value of equity = Stockholder's Equity (*SEQ*) [or Common Equity (*CEQ*) + Preferred Stock Par Value (*PSTK*) or Assets (*AT*) − Liabilities (*LT*)] − Preferred Stock + Balance Sheet Deferred Taxes and Investment Tax Credit (*TXDITC*) if available − Post Retirement Asset (*PRCA*) if available (Fama & French, 2001).

Preferred Stock = Preferred Stock Liquidating Value (*PSTKL*) OR Preferred Stock Redemption Value (*PSTKRV*) OR Preferred Stock Par Value (*PSTK*).

Market value of equity = Price (*PRC*) × Number of shares outstanding (*SHROUT*).

Same book value of equity is used for the reporting month as well as for the prior 11 months, i.e., for all 12 months of the reporting fiscal year.

Change in earnings (ΔEarnings): Absolute value of percentage change in annual earnings per share (*EPSPX*) over the year.

Dispersion in analyst forecast error: Difference between 75th and 25th percentile of analyst forecast errors.

Earnings Standard Deviation: Five-year (from year $t-4$ to year t) rolling window standard deviation of earnings per share (*EPSPX*).

Economic Policy Uncertainty (EPU) Index: A proxy of aggregate policy related uncertainty. This index is developed by Baker, Bloom, and Davis (2016) and designed to capture uncertainty about who will make economic policy decisions, what economic policy actions will be undertaken and when, and the economic effects of policy actions. The EPU index includes various categories of economic policies as shown below.

- Monetary policy
- Fiscal policy
- Taxes
- Labor regulations
- Legal Policy
- Competition Policy
- Government spending
- Health care programs and regulations
- National security and terrorism
- Trade Policy
- Energy & environmental regulation, natural resources and commodities
- Entitlement programs, social safety net, welfare programs
- Financial regulation (including banking and equity markets)
- Political conflict and leadership changes
- Sovereign debt, exchange rate policy, foreign reserves
- Other policy matters

The EPU index is constructed as a weighted average of four components on three types of measures after each component is standardized and normalized. The first component (the first type of measure) is based on the frequency of news articles on policy uncertainty found in 10 leading newspapers. The second component (the second type of measure) is drawn on reports by the Congressional Budget Office and this component is based on the dollar impact of the uncertainty about changes in tax code provisions that is about to expire in near future. The third and the fourth components (the third type of measure) are drawn upon the quarterly forecasts from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. The third component is based on the dispersion in forecasts about the consumer price index (CPI). The fourth component is based on the dispersion in forecasts about the expenditures by the local, state, and federal governments. On the overall index, these four components weigh 1/2, 1/6, 1/6, and 1/6, respectively.[13]

Idiosyncratic risk: Standard deviation of the regression residuals obtained from the market model (CAPM). A minimum of 15 daily return data and non-zero trading volume in a month are required to reduce the impact of small sample on the statistical power of the results. Standard deviation of daily residuals is multiplied by the square root of the number of observations in that month to obtain the standard deviation at monthly level.

Leverage: Monthly leverage is calculated as total debt divided by sum of total debt and market value of equity (MVE). Total debt is the summation of current debt (*DLC*) and long-term debt (*DLTT*). Same total debt is used for all 12 months of the reporting fiscal year. Monthly MVE is the product of price and number of shares.

Past Returns: Average of buy-and-hold returns over the last 12 months.

Volatility of analyst forecast error: Standard deviation of analyst forecast error.

Appendix B: Measures of Macroeconomic Condition

B1. Measures of general economic condition

Real GDP (Real Gross Domestic Product): Inflation adjusted value of the goods and services produced by labor and property located in the United States. The time series GDPC1 obtained from the Federal Reserve Bank of St. Louis.

Forecast for GDP growth rate (forecast for ΔGDP): Mean value of forecasts for 12-month ahead GDP growth rate. The time series obtained from the Livingston Survey of the Federal Reserve Bank of Philadelphia.

[13] While constructing the index, Baker, Bloom and Davis take care of concerns on validity of the measure in various ways. For example, to address the concern on errors arising from automated search, human audit on the search results are done. Concern on validity of EPU as a measure of uncertainty is addressed by high correlation between EPU and VIX, a common measure of uncertainty. To address the concern on potential political bias in news reporting, BBD split the 10 newspapers into five left-leaning and five right-leaning newspapers using the media slant index (Gentzkow and Shapiro 2010).

US Leading Index: The leading index for each state predicts the six-month growth rate of the state's coincident index.[14] In addition to the coincident index, the models include other variables that lead the economy: state-level housing permits (1 to 4 units), state initial unemployment insurance claims, delivery times from the Institute for Supply Management (ISM) manufacturing survey, and the interest rate spread between the 10-year Treasury bond and the 3-month Treasury bill. The Leading Index for the United States (USSLIND) time series obtained from the Federal Reserve Bank of St. Louis.

Composite Leading Indicators (CLI): CLI is built to provide early signals of turning points in business cycles showing fluctuation of the economic activity around its long-term potential level. The Composite Leading Indicators (CLI) time series obtained from OECD data. The components of the CLI are time series that exhibit leading relationship with the reference series (GDP) at turning points. The components of the CLI for USA are Work started for dwellings, Net new orders on durable goods, Share prices: NYSE composite, Consumer Confidence indicator, Weekly hours worked - manufacturing, Industrial confidence indicator - manufacturing, and Spread of interest rates.

Financial stress indicator: The Financial Stress Index (STLFSI) obtained from the Federal Reserve Bank of St. Louis. The index measures the degree of financial stress in the markets and it is constructed from 18 weekly data series that include seven interest rate series, six yield spreads and five other indicators. Each of these variables captures some aspect of financial stress. The interest rate series are effective federal funds rate, 2-year Treasury, 10-year Treasury, 30-year Treasury, Baa-rated corporate, Merrill Lynch High-Yield Corporate Master II Index, and Merrill Lynch Asset-Backed Master BBB-rated. The yield spreads are: yield curve (10-year Treasury minus 3-month Treasury), corporate credit risk spread (corporate Baa-rated bond minus 10-year Treasury), high-yield credit risk spread (Merrill Lynch High-Yield Corporate Master II Index minus 10-year Treasury), 3-month LIBOR-OIS spread (3-month London Interbank Offering Rate–Overnight Index Swap spread), TED spread (3-month Treasury-Eurodollar spread), and commercial paper spread (3-month commercial paper minus 3-month Treasury bill). The five other indicators included in the index are: J.P. Morgan Emerging Markets Bond Index Plus, Chicago Board Options Exchange Market Volatility Index (VIX), Merrill Lynch Bond Market Volatility Index (1-month), 10-year nominal Treasury yield minus 10-year Treasury Inflation Protected Security yield (breakeven inflation rate (10-year)), and S&P 500 Financials Index.

B2. Measures of economic uncertainty

Dispersion in forecasts for GDP growth rate: The time series obtained from the Livingston Survey of the Federal Reserve Bank of Philadelphia captures the variability in forecasts for 12-month ahead GDP growth rate. The dispersion measure is the difference between the 75th percentile and the 25th percentile of projections for GDP growth.

VXO implied volatility index: The CBOE S&P 100 Volatility Index VXO, obtained from the Federal Reserve Bank of St. Louis, is meant to reflect investors' expectations for short-term (30-day) volatility in the stock market.

[14] The Federal Reserve Bank of Philadelphia produces a monthly coincident index for each of the 50 states. The coincident indexes combine four state-level indicators: nonfarm payroll employment, average hours worked in manufacturing by production workers, the unemployment rate, and wage and salary disbursements deflated by the consumer price index (U.S. city average).

Cross-sectional standard deviation in firm-level monthly stock returns: Standard deviation of monthly stock returns at the cross-section is meant to capture the volatility in the stock market.

JLN uncertainty measure: A comprehensive uncertainty measure developed by Jurado, Ludvigson, and Ng (2015) and designed to capture the predictability of the economy.

Appendix C: Business Cycles

C1. Financial business cycles

Default spread (DEF): Yield spread between Moody's seasoned Baa and Aaa corporate bonds obtained from the Federal Reserve Bank of St. Louis.

Term spread (TERM): Yield spread between the ten-year and the one-year government bonds obtained from the Federal Reserve Bank of St. Louis.

One-month Treasury bill rate (TB): The risk-free interest rate (TB) is the one-month Treasury bill rate obtained from Kenneth R. French's data library.

Dividend yield (DIV): S&P 500 dividend yield obtained from the multpl.com website.

C2. Macroeconomic business cycles

Inflation rate: Monthly growth rate of Consumer Price Index for All Urban Consumers All Items (CPIAUCNS) obtained from the Federal Reserve Bank of St. Louis.

Unemployment rate: Monthly Civilian Unemployment Rate (UNRATE) obtained from the Federal Reserve Bank of St. Louis.

Growth rate in industrial production: Change in monthly Industrial Production Index (INDPRO) obtained from the Federal Reserve Bank of St. Louis.

C2. Recession indicator

NBER recession indicator data (USREC), obtained from the Federal Reserve Bank of St. Louis, is used to represent economic condition. The monthly time series denotes the months of recession (trough) by recession dummy = 1 and non-recessionary months (peak) by recession dummy = 0.